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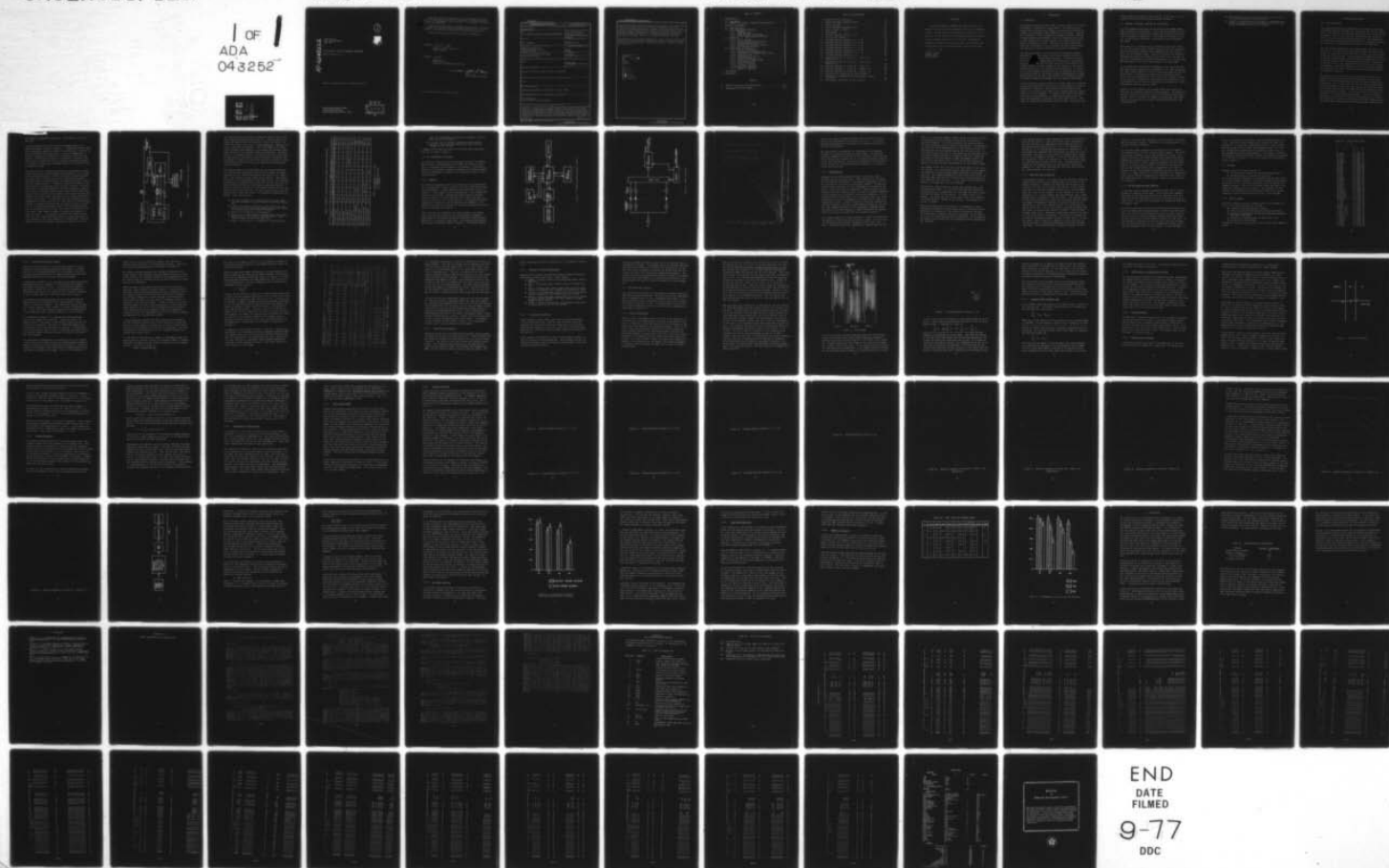
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Final Technical Report
June 1977

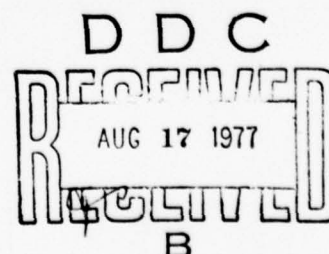
VOICE CONTROL SYSTEMS FOR AIRBORNE ENVIRONMENTS

SCOPE Electronics, Inc.



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ROME AIR DEVELOPMENT CENTER
Air Force Systems Command
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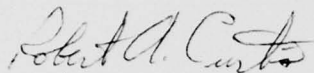
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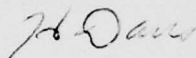
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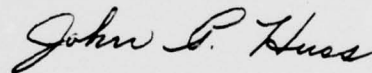
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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER RADC-TR-77-189	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) VOICE CONTROL SYSTEMS FOR AIRBORNE ENVIRONMENTS		5. TYPE OF REPORT & PERIOD COVERED Final Technical Report 5 Jan 76 - 4 Jan 77
		6. PERFORMING ORG. REPORT NUMBER 6205-0377
7. AUTHOR(s) Hill Montague		8. CONTRACT OR GRANT NUMBER(s) F30602-76-C-0127
9. PERFORMING ORGANIZATION NAME AND ADDRESS SCOPE Electronics, Inc. 1860 Michael Faraday Drive Reston, VA 22090		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 62702F 40270511
11. CONTROLLING OFFICE NAME AND ADDRESS Rome Air Development Center (IRAP) Griffiss AFB NY 13441		12. REPORT DATE June 1977
		13. NUMBER OF PAGES 92
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office) Same		15. SECURITY CLASS. (of this report) UNCLASSIFIED 15a. DECLASSIFICATION/DOWNGRADING SCHEDULE N/A
16. DISTRIBUTION STATEMENT (of this Report) Approved for public release; distribution unlimited.		
17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report) Same		
18. SUPPLEMENTARY NOTES RADC Project Engineer: Captain Robert A. Curtis (IRAP)		
19. KEY WORDS (Continue on reverse side if necessary and identify by block number) Word Recognition g-force stress on word recognition		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) The effects of g-force stress on human voice patterns were investigated with the objective of finding means for making isolated word recognition word devices work in the fighter aircraft cockpit environment. Data were taken in a human centrifuge with SCOPE Electronics Inc's Voice Data Entry System (VDETS) used to prompt and pace the subjects. Data were subsequently digitized and stored for analysis and recognition experiments using the VDETS algorithm with a number of variations. (Cont'd)		

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Recognition performance on the centrifuge data was initially poor. Means were found for improving it substantially through modifications to the VDETS algorithm and through preprocessing techniques. VDETS modifications included increased coding resolution, improved segmentation techniques and provision for multimode training. Breathing noise elimination and inverse filtering preprocessing routines were effective. Variations in spectral characteristics with g-force stress were found, but no consistent pattern was discerned.

The effectiveness of the inverse filtering led to the conclusion that the major problem was the face mask worn by the subjects, causing a variable element in the acoustic transmission path. Additional work will be required to eliminate face mask effects.

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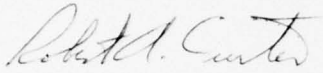
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EVALUATION

A study was conducted to determine the effects of g-stress on a speaker's voice patterns and the subsequent effect on word recognition accuracy. Data was obtained on nine subjects at g-levels, 1G, 3G, 5G and at 7G. All the subjects wore a face mask and made several repetitions of the digits (except at 7G) in a 13° seat. Algorithms were developed to compensate for the major problems caused by breath noise and the change of the voice characteristics caused by the face mask.



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1. INTRODUCTION

1.1 BACKGROUND

Considerable progress has been made in recent years in the field of automatic recognition of human speech. The point has been reached where isolated word recognition devices are feasible for a number of applications both commercial and military. However, these automatic speech recognition equipments generally require a benign operating environment, where the signal-to-noise ratio is good (greater than 20 dB) and where the transmission path is subject to complete control. There are military applications where the environment is not so benign, but where voice recognition capability could be effectively utilized if available.

One such application is in the cockpit of a fighter aircraft, where the requirement exists for a voice command system for a pilot to make his mission more effective. A number of aspects of the cockpit environment make it difficult for a voice recognition system. One of these that has long been considered to be a major obstacle to voice command in the cockpit is the g-force experienced by the pilot during aircraft maneuvers. The objective of the research reported here was to determine the effects of g-force stress on the pilots' speech characteristics so that these effects can be taken into account in the design of automatic speech recognition equipment for the airborne environment.

A major effect of g-force stress on the human body is the tendency to force blood away from the brain causing blackout, which is tantamount to fainting. Most subjects can withstand g-force stress up to about 3g when seated in an upright position without effort or risk of blackout. At higher stress levels the subject must work to avoid blackout by tightening the muscles on his chest and diaphragm to constrict the blood vessels there. This tends to prevent the blood drain from the head. The subject may

become winded as a result of this effort. At any rate it is not conducive to maintaining consistent speech patterns.

1.2 SUMMARY OF METHODS, RESULTS AND CONCLUSIONS

For this program a data base was collected on the human centrifuge at Brooks Air Force Base. A voice recognition device, SEI's VDETS, was used to prompt the subjects and to provide an on-line test of recognition capability. Data from nine subjects at 1g, 3g, 5g, and 7g were collected. Good quality audio recordings were made.

Subsequently the recordings were processed through SEI's VDETS and the raw spectral data, normally collected by that device and used for further processing, were transferred to and stored in SEI's DEC-10 computer system. Routines to emulate the VDETS recognition algorithm and a number of variations on it, as well as routines to preprocess the data and to analyze it in various ways were developed on the DEC-10 and applied to the data base.

It was found that recognition performance on the centrifuge data was significantly poorer than performance on the same vocabulary but under normal conditions with the microphone supplied with the VDETS system. Performance decreased with increasing g-force stress, but was comparatively poor even at the 1g level for most of the subjects. Substantial improvements were obtained by various modifications to the basic recognition algorithm but a fully satisfactory solution was not found.

Changes in voice patterns with g-force stress were found, but there was no consistent pattern to these changes. The underlying physical causes of the effects were not definitely established. However, there is evidence to support the conclusion that difficulties in recognizing the g-force stressed word patterns were attributable to:

- Breathlessness on the part of the subject as a result of the efforts required to avoid blackout.
- Variable modifications of the acoustic transmission path caused by changes in the cavity formed by the face mask around the mouth and nose of the subject.

2. TECHNICAL DISCUSSION

2.1 DATA COLLECTION

The principal data for the program were collected at the Human Centrifuge facility at Brooks Air Force Base, San Antonio, Texas. All of the subjects were from the regular pool for centrifuge experiments. In all, nine subjects each provided one series of runs. There were seven subjects dedicated to this program and two additional subjects who were involved in a different program, but were able to provide some voice data at the same time.

For the subjects dedicated to the program runs were made at 3g, 5g, and 7g. The seat in the centrifuge gondola was set at the normal 13° angle and the subjects wore the RAF type PQ face mask with built-in microphone. The non-dedicated subjects were testing an experimental helmet and face mask designated MBU 5/P, and of course, used this for the voice data collection. These subjects had to make a run through which the g-levels were varied to simulate a particular maneuver, and they could not provide voice data at this time. Hence less data was obtained from the non-dedicated subjects.

The original plan for the data collection effect called for a vocabulary of words and phrases representative of those that might be useful for voice cockpit control functions under real conditions. As it turned out, the time available on the centrifuge was limited to one week, there was not an unlimited supply of subjects, and the time that each subject can spend at levels of 5g and above is limited. At 5g each subject is allowed 30 seconds at a time and one minute per day. In view of these restrictions it was decided to limit the vocabulary to 10 words, the digits zero to nine, on the grounds that many samples of the same word under various conditions would be more valuable than a

like number of different utterances. This proved to be a wise decision.

A block diagram of the setup used for recording data in the human centrifuge is shown in Figure 1. A SCOPE Electronics VDETS voice recognition device was used in the experiment. This device will be described more fully later. One of its components, a self-scan display, was mounted in the gondola in front of the subject. This display provides 16 alphanumeric characters that can be used to prompt the subject, indicate recognition results, or provide any other type of message that can be contained in the 16 character format.

The audio from the face-mask microphone was fed through a preamplifier part of the normal gondola instrumentation, to the input of the VDETS contained in the same box as the self-scan display. The VDETS channel provides gain and an adjustable attenuator. The VDETS output was fed through a coax channel via slip rings to the main VDETS processor. A parallel signal was provided to the right channel of a Wollensak Type 6250 tape recorder. The voice output of the gondola preamplifier was also transmitted through slip rings to the normal audio channels used with the centrifuge system. These channels provide mixing of the audio from the gondola with the audio from a microphone in the control room used to instruct the subject. The combined audio was recorded on an instrumentation recorder and also the left channel of the Wollensak Recorder. Previous experience had indicated a source of distortion in the amplifiers normally used in the centrifuge system. Also it was desirable not to have the control room audio on the voice data. Some care was taken to separate the channels as shown in Figure 1. The distortion problem was cleared up, but there was still some feedthrough from the control room mike to the voice data in the right channel of the Wollensak. This was solved by keeping the control room mike off during test runs.

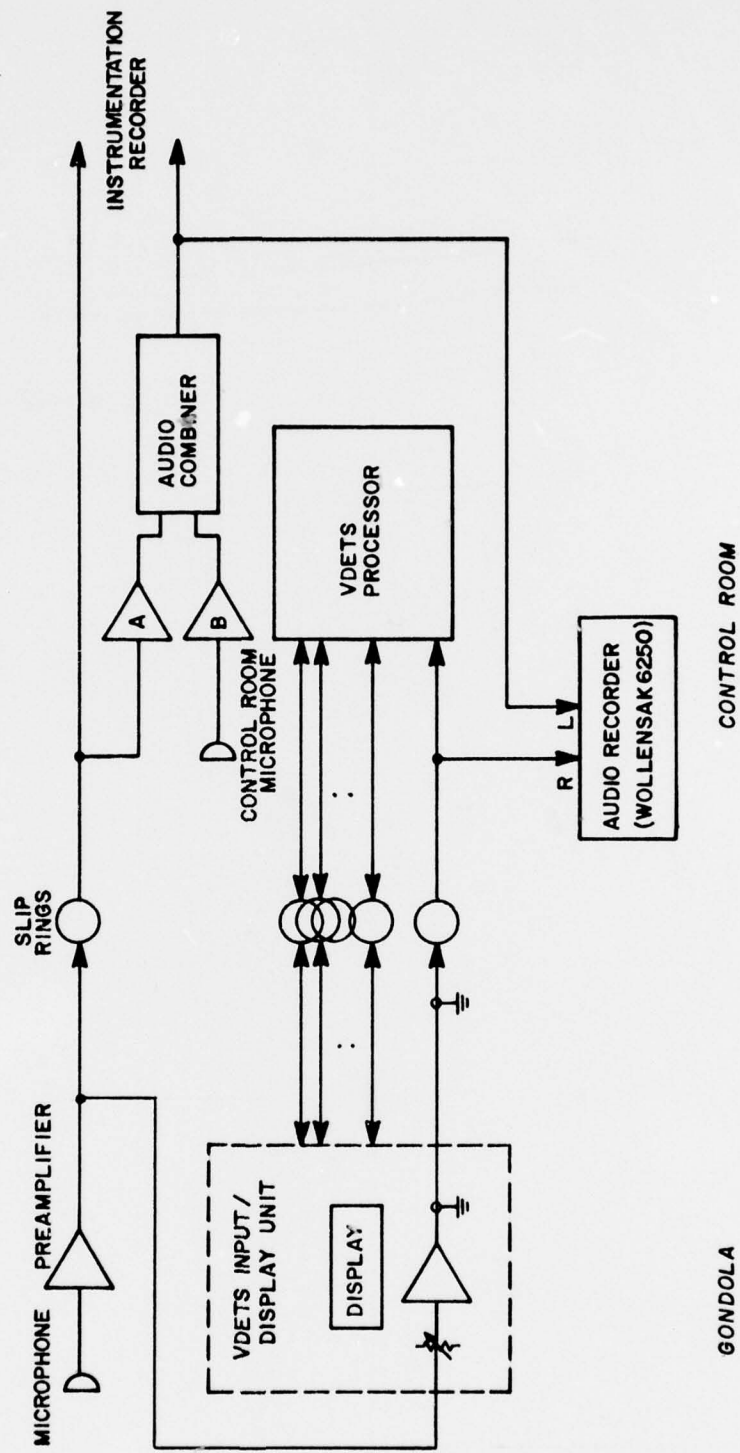


Figure 1. Setup for Data Collection

The VDETS self-scan was used to prompt the subject and to indicate recognition results during the test. The next word to be spoken was displayed on the self-scan. After the subject had spoken that word, a "C" or an "X" was displayed to indicate correct or incorrect recognition. Use of the VDETS in the data-taking provided some feedback to the subject and perhaps added some interest to the experiment from his standpoint. The major function it provided, however, was to pace the rate of speaking. In some previous experiments, where the subject had merely been instructed to repeat the digits over and over, the rate of speaking turned out much too fast for an isolated word recognition system to follow.

The subjects used in the experiment had no previous experience with word recognition devices and had little chance to become familiar with the VDETS system during the course of the experiment. The procedure in most cases was as follows. The subject was given a brief explanation of the VDETS system. The training and recognition functions were explained. He was then given one practice run consisting of five training passes and several passes through the word list to familiarize himself with the display and the system operation. He then took his position in the gondola and the door was closed. All subsequent passes were recorded. These consisted of:

- Five and sometimes ten training passes with the words repeated in order at 1g acceleration (centrifuge stationary).
- Eight to ten passes through the word list at 1g. For these passes the subject was prompted and the word order was varied through ten different sequences.
- Eight to ten passes at 3g acceleration.
- Two runs at 5g acceleration of approximately 30 seconds duration each. This usually provided time for four passes through the word list each time.
- Eight to ten passes at 1g immediately following the 5g

TABLE I. SUMMARY OF DATA COLLECTED ON BROOKS AFB HUMAN CENTRIFUGE

SUBJECT	DATE	NUMBER OF REPETITIONS							MIKE
		TRAIN	1G	3G	5G	5G	1G	7G	
1) DAVID STONER	7/19	5	5	4+, 5	4	4+	10	0+	RAF PQ
2) JERRY WHITE	7/20	10	5	8	4	4	8	2+	RAF PQ
3) ERWIN RAMPY	7/20	10	5	8	4	4	8	0+	RAF PQ
4) LLOYD GERKIN	7/20	10	5	8	3+	ABORTED	ABORTED		RAF PQ
5) JOHN BRANCH	7/20	5	5	6	3+	3+	8	1+	RAF PQ
6) GEOFFRY SANDERSON	7/20	5 W/RT	5	9+	5+	3	6+		MBU 5/P
7) HOWARD MAJER	7/20	5	5	7+	9+				MBU 5/P
8) KEN GILLINGHAM	7/21	5+ W/RT	5+, 4 3+	8+	4	5+	8		RAF PQ
9) STEVE SEXAUER	7/21	5	6+	8+	1X, 4-	4	8+	1	RAF PQ

NOTES: EACH REPETITION = 10 WORDS

X = ABORTED

± = PARTIAL REPETITION

RT = RETRAIN

runs. In most cases the subject was somewhat winded at the start of these passes.

- A 7g run with the subject repeating as many words as possible. About one pass through the word list was average for the 7g runs.

A summary of the data collected at the Brooks Human Centrifuge Facility is shown in Table I.

2.2 DATA PROCESSING FACILITIES

Facilities for processing the speech data consisted of hardware and software. Existing SEI test equipment and computers were used. No hardware was developed on the program. A substantial amount of the software, consisting primarily of FORTRAN programs for SEI's DECSYSTEM-10 computer, was developed as part of the program effort.

2.2.1 Hardware

The principal equipment used for processing of the speech data was the development support system for the SEI VDETS voice recognition equipment. A block diagram of the VDETS DSS is shown in Figure 2. A Data General NOVA 2 minicomputer is the central processor for the system. Standard peripheral devices include a teletype terminal, a high speed paper tape reader and punch, a cassette tape unit, and a Linc tape unit. The system has a 9600 baud RS-232 interface to the SEI DECSYSTEM-10 computer. This interface was used for transmitting raw data from the NOVA to the DEC-10 for storage and analysis.

Also interfaced to the NOVA in the VDETS system is the speech processing front end shown in the block diagram of Figure 3. Audio input to the speech processing front end is amplified and applied to a 16 channel filter bank. The bandpass characteristics of these filters are shown in Figure 4. The filter outputs

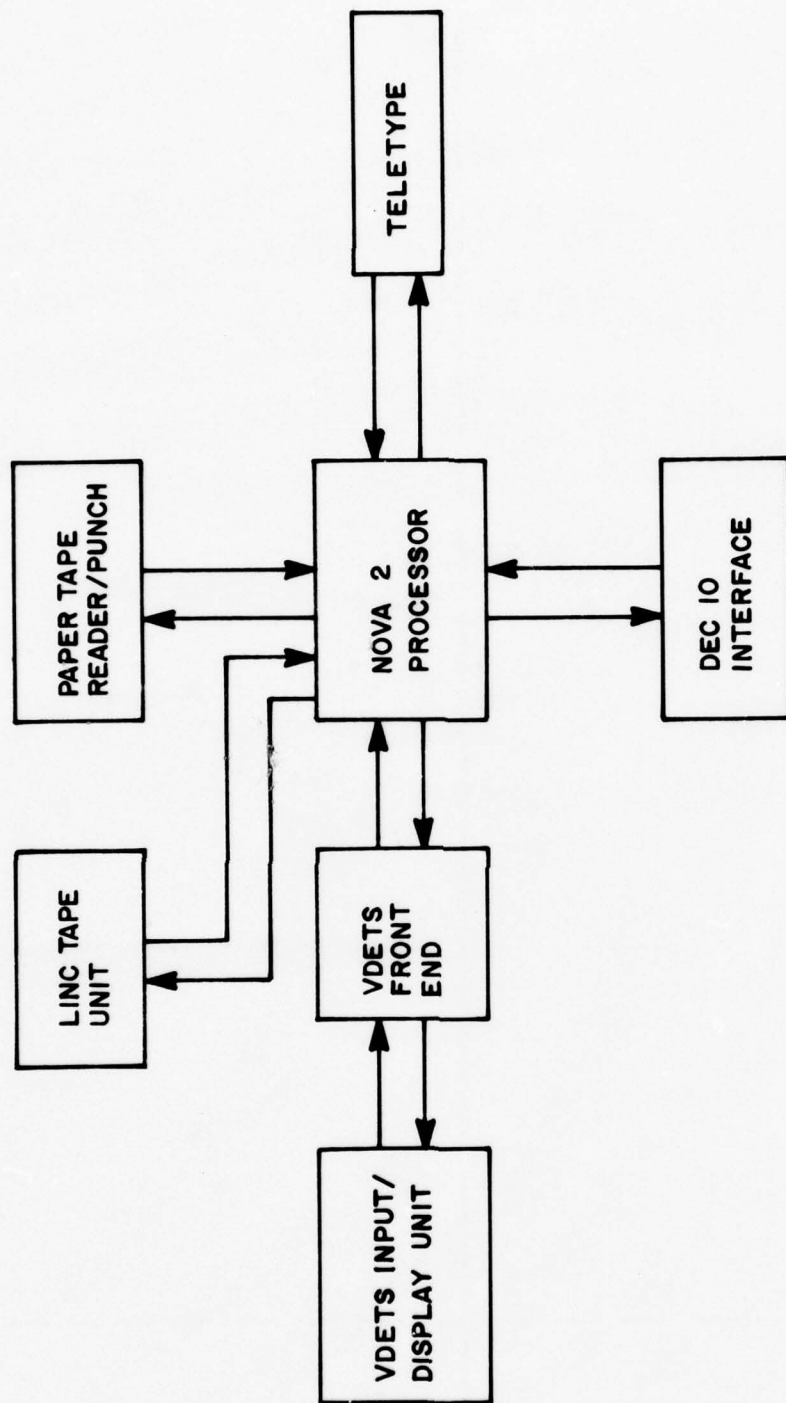


Figure 2. VDETS Development Support System

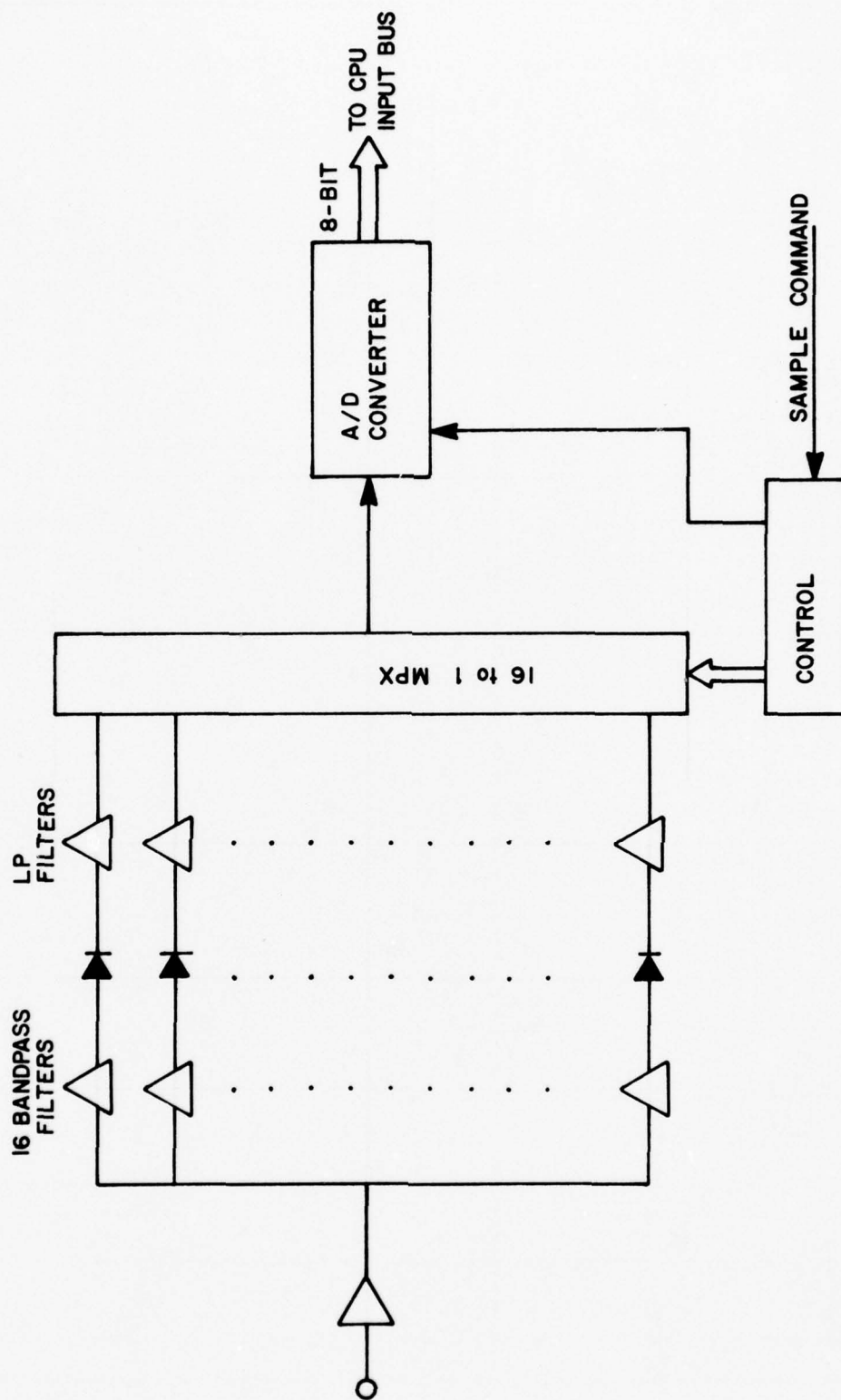


Figure 3. VDETS Front End

DSS 3/4/76 FILTERS

FILTER C.F. B.W. AMP.

1	1741	2132	.178
2	2146	2301	.122
3	844	397	.109
4	1025	368	.113
5	1114	227	.126
6	1353	329	.161
7	2182	1550	.213
8	2335	1073	.243
9	2455	1300	.300
10	2638	1114	.348
11	2774	697	.370
12	3353	1239	.457
13	3898	1284	.535
14	4367	1310	.661
15	5000	1321	.796
16	5789	1323	1.000

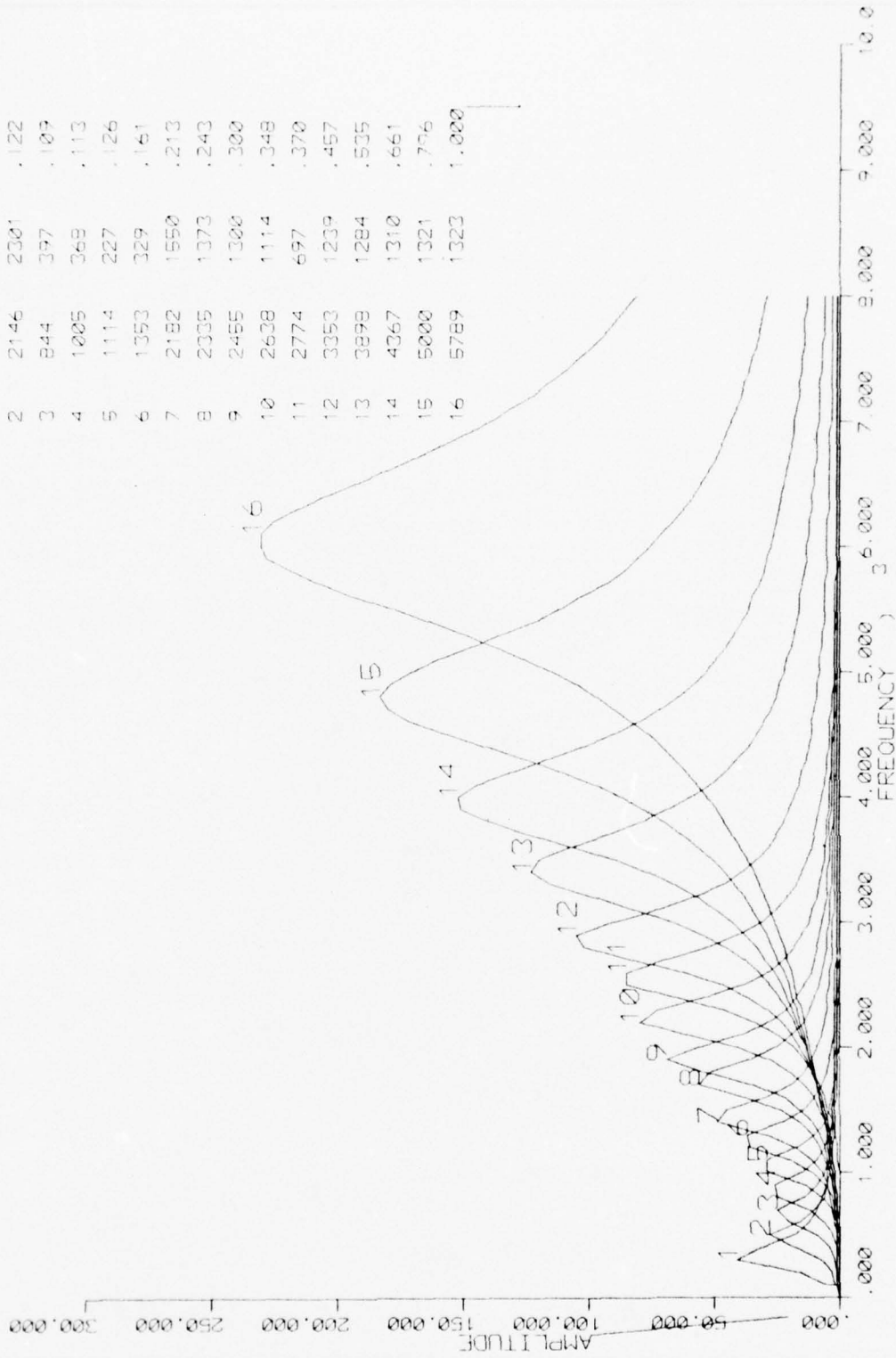


Figure 4. Filter Bandpass Characteristics

are detected and the detected outputs are filtered in low pass filters of approximately 25 Hz cutoff frequency. The detected and filtered outputs are fed through a 16 channel multiplexer to an 8 bit A/D converter.

The speech front end processor is interfaced to the computer through a NOVA general purpose interface board. Through this interface commands can be given to the multiplexer to control the filter channel to be sampled and to the analog-to-digital converter to begin conversion. At the end of conversion the digitized output as well as an end-of-conversion indication is available on the NOVA input bus.

2.2.2 VDETS Software

Software for the VDETS system includes a proprietary core-resident operating system, VOICE. VOICE contains the algorithm for training and recognition of designated vocabularies, as well as the routines to service all peripheral devices. In addition, VOICE contains provision for user programming of vocabulary and action. The actions may be triggered by various events, such as interrupt from an external device, the end of a training sequence, or the recognition of a specific word in the vocabulary. If no specific action is associated with a vocabulary word, then a general default action is triggered at the completion of each word recognition process. Action triggers may cause the execution of routines written in the special programming language of the system. The commands available in the programming language permit retrieval of the word recognized, simple arithmetic and logical functions, as well as control of the peripheral devices.

As a simple example of a voice program, consider the one used for the Brooks Air Force Base data collection effort. In this case, the vocabulary was the digits arranged in order "one, two, ..., zero." The train action was controlled by command from the con-

sole, i.e. typing the command "TRAIN" causes the system to clear out previously stored reference patterns and initiate a new training sequence. To initiate training, the system displays the first vocabulary word on the self-scan device. On detecting an utterance, the system processes it and stores the result as the beginning of the reference pattern for the first word. It then displays the next word in the vocabulary and continues until a number of passes through the vocabulary have been completed. The number of training passes is under programmer control; in this case it was set to five. At the end of the training sequence the system displays "END TRAIN" on the self-scan display.

The command "UPDT" will initiate a one-pass update to the training process. In the updating process, data from the new samples are combined with that already stored to modify the reference patterns. The command "RETRAIN" will cause the system to ask for the word number and then to initiate a new training sequence of five passes on that word only. In this case, the old reference pattern is cleared and a new one generated.

Following the end-of-train the system goes automatically into the recognition mode. In the recognition mode the system can operate either in a prompt mode or a no-prompt mode fed by entering "PRM" or "NPRM" on the console. The default mode is no-prompt. The system can also be put into a stop or go condition by typing "STOP" or "START" on the console. The default condition is "START."

When the system detects an utterance, it automatically goes through the recognition process and finds the word most closely matching this utterance in its library of reference patterns. Following this the default action is triggered. If the system is in the "GO" condition and the no-prompt mode, then triggering the default action causes the word recognized to be displayed on the self-scan.

In the prompt mode the system displays the next word expected on the self-scan display. Under the default action triggered by the next utterance, it compares the word recognized with the word expected and displays either a "C" or "X" depending on whether or not the recognized word matched the expected one. It then updates the expected word and displays the next one on the self-scan. The order in which words are prompted goes through a cycle of ten passes as follows: On the first pass the words are presented in order one through ten. The second pass begins with two and goes in steps of three, etc. The sequence can be started at the beginning of any of ten orders by typing the command "I." The system then asks for the first word and sets the prompt sequence for that point.

2.2.3 VDETS Raw Data Processing

As described previously, the VDETS front end contains a spectrum analyzer whose output can be sampled under the control of the central processor. Normally the sampling process goes on continuously at a rate of 100 samples per second. At each sample point all 16 filters are sampled resulting in 16 8-bit numbers which are input to the computer. If the system is in an idle condition, i.e. no word boundary has been detected, then a word boundary test is applied to each new sample. The absolute value of the spectral difference between the new sample and the preceding sample is computed by summing the absolute values of the difference in the filter outputs over the 16 filters from one sample to the next. If the sum exceeds a certain threshold then the sample is retained and stored in a buffer. Then the word boundary flag is set. Subsequent samples are tested in the same way and either stored or rejected. (A different threshold can be used for subsequent samples although in most cases it is kept the same.) When a total of 16 samples in a row have been rejected, the word is considered terminated and the word boundary flag reset. If the total number of samples retained by this

process is less than some threshold, then the buffer is cleared and the utterance ignored. Otherwise the system proceeds to process the word just received.

The raw data buffer provides for storage of up to 96 samples, each consisting of 16 8-bit spectral energy numbers. The buffer can contain, therefore, up to 1536 characters or bytes. The special version of the VOICE software that supports the DEC-10 communication interface also contains a special set of actions that can be used in a user generated program to initiate transmission of various types of data. One such action causes the data in the raw data buffer to be transmitted to the DEC-10. Another special action permits information stored in user locations, i.e. under control of the user program, to be transmitted. Other actions control transmission of data from other stages in the VDETS processing. These actions, however, were not used on this program.

2.2.4 DEC-10 Communications Software

At the other end of the data transmission path, DEC-10 routines provide for handling speech data. The routines most commonly used take the received data and pack the characters four to a word (the DEC-10 word length is 36 bits) and store the data in a disk file. The data can subsequently be transferred from disk to magnetic tape.

All of the data from the Brooks Centrifuge Experiment were processed as described above and stored in files on the DEC-10 system. The process of transcribing data from the audio tapes to the DEC-10 in this way was somewhat tedious because the transmission process was not fast enough to operate in real time. It was necessary, therefore, to stop and start the tape recorder, waiting between each word for the transmission process, which took approximately three to five seconds. It was necessary, of

course, to supply with each word a label indicating which word it is. This can be done automatically through the VDETS user program if the words are repeated reliably in a known sequence. With the Brooks data the order was supposedly known, but there were enough gaps, repetitions and extraneous noises, etc., to make automatic labeling unsatisfactory. Each sample, therefore, was manually labeled after entry through a CRT terminal connected in to the DEC-10 system. A list of the data files processed is shown in Table II.

2.3 SOFTWARE

Software used in the study consists of

- the VDETS voice routine with several modifications
- FORTRAN routines to operate on the DEC-10

The VOICE operating system and its modifications are done entirely in NOVA assembly language. Application programs as mentioned in Section 2.2.2 in the VOICE system use their own special programming language. Most of the software effort and most of the study were carried out on the DEC-10. The remainder of this section will be devoted to a description of the DEC-10 speech processing library developed for and used on this program.

2.3.1 DEC-10 Library

The DEC-10 speech processing library used on this program consists of the following types of routines:

- A master training/recognition routine
- Various routines for preprocessing speech data files
- Routines for examining, editing and otherwise manipulating speech data files
- Routines for analyzing data in speech data files
- Routines for plotting data

Annotated listings of these routines are included under separate cover.

TABLE II. LIST OF DATA FILES

FILE LIST					
N	SUBJECT	T	G	F	W
U		A	F	I	R
M		P	D	L	D
		E	R	E	S
1	STONER	1	1	TRF07	95
1	STONER	1	1	TRF25	95
1	STONER	1	1	TRF02	52
1	STONER	1	1	TRF01	50
1	STONER	1	3	TRF03	93
1	STONER	1	5	TRF04	83
1	STONER	1	7	TRF06	5
2	WHITE	1	1	TRF11	86
2	WHITE	1	1	TRF08	160
2	WHITE	1	3	TRF09	81
2	WHITE	1	5	TRF10	85
3	RAMPY	2	1	TRF15	83
3	RAMPY	2	1	TRF12	143
3	RAMPY	2	3	TRF13	79
3	RAMPY	2	5	TRF14	84
3	RAMPY	2	7	TRF16	9
4	GERKIN	2	1	TRF17	123
4	GERKIN	2	3	TRF18	79
4	GERKIN	2	5	TRF21	32
5	BRANCH	2	1	TRF25	82
5	BRANCH	2	1	TRF20	101
5	BRANCH	2	1	TRF19	50
5	BRANCH	2	3	TRF22	60
5	BRANCH	2	5	TRF24	30
5	BRANCH	2	5	TRF23	34
5	BRANCH	2	7	TRF26	10
6	SANDERSON	3	1	TRF28	50
6	SANDERSON	3	1	TRF27	50
6	SANDERSON	3	1	TRF30	61
6	SANDERSON	3	3	TRF29	82
6	SANDERSON	3	5	TRF31	54
6	SANDERSON	3	5	TRF32	30
7	MAJER	3	1	TRF33	50
7	MAJER	3	1	TRF34	50
7	MAJER	3	1	TRF36	92
7	MAJER	3	3	TRF35	78
8	GILLINGHAM	3	1	TRF37	50
8	GILLINGHAM	3	1	TRF38	54
8	GILLINGHAM	3	1	TRF39	32
8	GILLINGHAM	3	1	TRF40	31
8	GILLINGHAM	3	1	TRF44	77
8	GILLINGHAM	3	3	TRF41	82
8	GILLINGHAM	3	5	TRF42	40
8	GILLINGHAM	3	5	TRF43	48
9	SEXAUER	4	1	TRF45	50
9	SEXAUER	4	1	TRF46	62
9	SEXAUER	4	1	TRF50	83
9	SEXAUER	4	3	TRF47	82
9	SEXAUER	4	5	TRF48	39
9	SEXAUER	4	5	TRF49	40
9	SEXAUER	4	7	TRF51	11

2.3.2 Training/Recognition Program

RESLT3, the final version of the training/recognition routine, performs a training and/or recognition experiment on a speech data file in the format developed for this program. The basic processes are patterned after the VDETS algorithm and there are numerous options for the various functions performed.

As described in Section 2.2.3, raw data for the speech processing algorithm consist of a number of 16-element spectral samples, each sample quantized to 8 bits. The raw data are reduced to a much smaller number of bits by the processes of segmentation, compression and coding. The output of this process is referred to as the coded data and is of fixed length for all words.

The segmentation process divides the set of raw data samples comprising a single utterance into a fixed number N , usually eight, of subsets or segments. The compression process averages the spectral samples in each segment to produce N averaged spectra. Finally the coding process reduces the N averaged spectra to the coded form with a further reduction in the bit level.

An alternative procedure is to perform the coding operation prior to the compression operation. Under this option, the coding process is performed on each raw data sample and the compression is performed by averaging the coded data samples over each segment rather than averaging the spectra. The motivation for this alternative mode is that it eliminates the need to store the raw data samples and hence reduces the memory requirements for the processor.

The algorithm for segmentation and coding as well as the number of bits used in the coded word are not described above because a number of options for these processes are available. During the course of the program, three algorithms for segmentation and ten algorithms for coding were tested. These are all available in

RESLT3 as well as the code-before-compress and code-after-compress modes discussed in the preceding paragraph. Details of the various processing modes are contained in Appendix A.

The training process generates the reference patterns or templates against which unknown words are compared during the recognition process. The reference patterns are generated from a set of training samples consisting of one or more repetitions of each word of the vocabulary.

RESLT3 provides a multi-mode training process as described in Appendix A under Reference Pattern Distance. Training may produce more than one reference pattern for each vocabulary word if the samples provided for training are sufficiently dissimilar. The reference pattern for a given word may be derived from a single training sample in which case the reference pattern is identical to the training sample. Usually, however, two or more training samples go into a reference pattern. In this case the coded words for all of the training samples used to generate a given reference pattern are compared element by element and elements that are not consistent over the set of training samples are masked out of the reference pattern.

In the recognition process the coded unknown word is compared with all reference patterns and a score generated for each comparison. Several modes for comparison as well as several modes for scoring are available, as discussed in Appendix A. The word recognized is that associated with the reference pattern that produces the highest score.

In the simplest combination of comparison and coding modes the unknown and the reference pattern are compared element by element and sample by sample over all unmasked elements of the reference pattern. The score is given by

$$\text{SCORE} = 128 (\text{NBA-HD}) / \text{NBA}$$

where NBA is the number of active (i.e. non-masked) elements in the reference pattern and HD is the hamming distance between unknown and reference.

RESLT3 provides data output as follows: For each utterance the data provided are the word and the sample numbers, the in-class score and the maximum out-of-class score, the number of the word recognized and the scores and word numbers for the five highest scoring comparisons. For each vocabulary word it provides the performance index, given by

$$PI = \frac{S_i - S_o}{\sqrt{\sigma_i \sigma_o}}$$

where S_i and S_o are the in- and out-of-class average scores, and σ_i and σ_o are the standard deviations of the in- and out-of-class scores over all samples of that word in the file. For each file it provides a summary including the means and standard deviations of the in-class scores and the maximum out-of-class scores, the overall performance index, defined as before, the recognition rate, and an error matrix. Also for each file it provides a header giving the file number for the unknown, either the reference pattern file number, if obtained from a different file than the unknown or the sequency numbers of the samples used for training if obtained from the same file, and identification of the modes used. A description of the modes is contained in Appendix A.

An example of the printout is shown in Figure 5. In this case the unknown file was WBT45.BIN and the experiment used the first five samples from that file for training and the remaining samples for recognition. The segmentation mode was 2 and filters 1-16 were used for the cumulative energy change segmentation algorithm. Eight segments were used. Other mode numbers are also indicated in the header.

For individual utterances the first two columns are the word and sample numbers. The next two columns are the maximum scores for in-class and out-of-class comparisons. The fifth column is the number of the word recognized, i.e. the word number associated with the maximum score. The next 15 columns are the word numbers, reference pattern numbers and scores for the five highest scores obtained on the utterance. For example the first entry indicates that sample 6 of word 1 was recognized as word 9 with a score of 108 (out of a maximum 128) for word 9 and a score of 97 for the best in-class comparison. The high scoring reference pattern was number 13, associated with word 9 and the next highest was number 9, associated with word 5. In this printout the option to print individual results for errors only was selected.

In this test the best performance index was 6.06 for word number 9. After the data for individual words, the next four numbers are the means and standard deviations of the in-class and maximum out-of-class scores for the test. In this case the mean in-class score was 114, the mean of the maximum out-of-class scores was 103 and the standard deviations were 11 and 10 respectively. These data are followed by the overall performance index (1.0488) and the recognition rate (82.26). Finally the error matrix shows a count of words recognized versus words spoken. For example, of the 6 samples of word number 1 spoken, 4 were recognized correctly and 2 were recognized as word number 9.

2.3.3 Preprocessing Routines

During the course of the program several routines were developed for modifying the data in speech data files. These routines read data from the original file and create a new file with the modified data. The order of the words and the word labeling remain intact. The principal preprocessing routines used were the breath noise eliminator, BNE1, the modified word boundary test, BWBT, and the inverse filtering routines SPEQ and SPEQA. The

nature and effects of these routines will be discussed in Section 2.4.

2.3.4 Analysis and Plotting Routines

Another set of routines was used for analysis and/or plotting of data from the speech data files. These include:

- CODEST - collects statistics on coded data from a speech data file
- FAPLT - Plots data from a spectral file on CALCOMP Plotter
- FILAV - Averages data from a speech data file and writes result in a spectral file suitable for plotting by FAPLT
- FILPLT - Plots data from a speech data file in the format of filter output vs time frame over all 16 filters
- SEGPLT - Plots data from a speech data file in the format of filter output averaged over each segment for eight segments and 16 filters
- SPPLTI - Prints time-frequency spectrograms of data from a speech data file on the line printer

2.3.5 File Editing Routines

Three routines, FILAS, DATED2, and FILED were used for editing of the speech data files. Each of these routines leaves the original file intact and writes the edited file as a new file. FILAS permits assembly of a new file from one or more old files. Words can be selected by word and sample number for inclusion in the new file.

FILED provides for modification of the header data in words in a file or deletion of words altogether. The principal use was for relabeling of words where known errors had been made in the original data transfer process.

The routine DATED2 provides for editing of the spectral data by elimination of frames. One command causes an intensity modulated spectral representation of the word to be displayed on the CRT. The word can be truncated by chopping off frames from the beginning or the end or the word can be eliminated altogether. The routine was initially developed for manual elimination of breathing noise from word samples. It later proved valuable for isolating samples of noise or specific phonemes for further analysis.

2.4 EXPERIMENTS AND RESULTS

This section will describe the experiments performed on the data base and the results obtained. The objectives of the experiments were to determine what, if any, differences there were in the speech patterns taken at different g-force levels and to improve the overall recognition result. The experimental work was done on the DEC-10 computer using the speech data files generated as described in Section 2.2.

2.4.1 Initial Experiments

The very first experiments were run on-line as the data were being collected. The VDETS system, installed as described in Section 2.1, provided recognition results on the CRT display as the words were being spoken in the centrifuge gondola. Prior to the start of the data gathering effort the system was checked out with a speaker seated in the centrifuge gondola and using the microphone normally supplied with the system. With the ten-word vocabulary the recognition rate of VDETS should have been near perfect, i.e. 99% or better. While no results were formally recorded, it was apparent that the machine was operating normally. The speaker could go through the word list at least ten times without error.

When the input to the machine was switched over to the face mask microphone that was to be used in the data gathering, the operation of the system was clearly degraded although again, no formal results were recorded. As the data gathering proceeded we attempted to mark score sheets for the first subject. There were five errors in five passes for the first 1g run for a recognition rate of 90%. This run was made immediately after the training process so that there was no g-force stress at all. During the 3g run for subject 1, there were 35 errors in 92 words for a recognition rate of 62%. With the errors coming this frequently, it was difficult to keep up with the score sheet and for most of the remaining subjects no scoring was recorded. Subject 7, however, one of the subjects using the experimental mask as described in Section 2.1, did somewhat better. For this subject the rate was 98% for the first 1g run of 50 words and 88% for the 3g run of 78 words.

When the tapes were received at the SEI facility and run through the VDETS development support system, similarly poor results were obtained. It was obvious that the breathing noise was contributing to the problem. The face mask used fits tightly around the nose and mouth so that practically all of the subject's air intake must pass through a supply tube approximately two feet in length with a diameter of about one inch. Even with the subject at rest there is a perceptible noise associated with a breath intake. The situation was worse during the g-force runs where the subject was somewhat winded as a result of his efforts to "get on top." The first step to a solution of the breathing noise problem was to print out spectrograms of some of the data. Figure 6 shows one of these with breathing noise clearly apparent. The next step was to manually edit out segments of breathing noise through the use of DATED2 as described in Section 2.3.5. In all cases the edited files provided better recognition rates than their unedited sources. The next step was to automate the editing process.

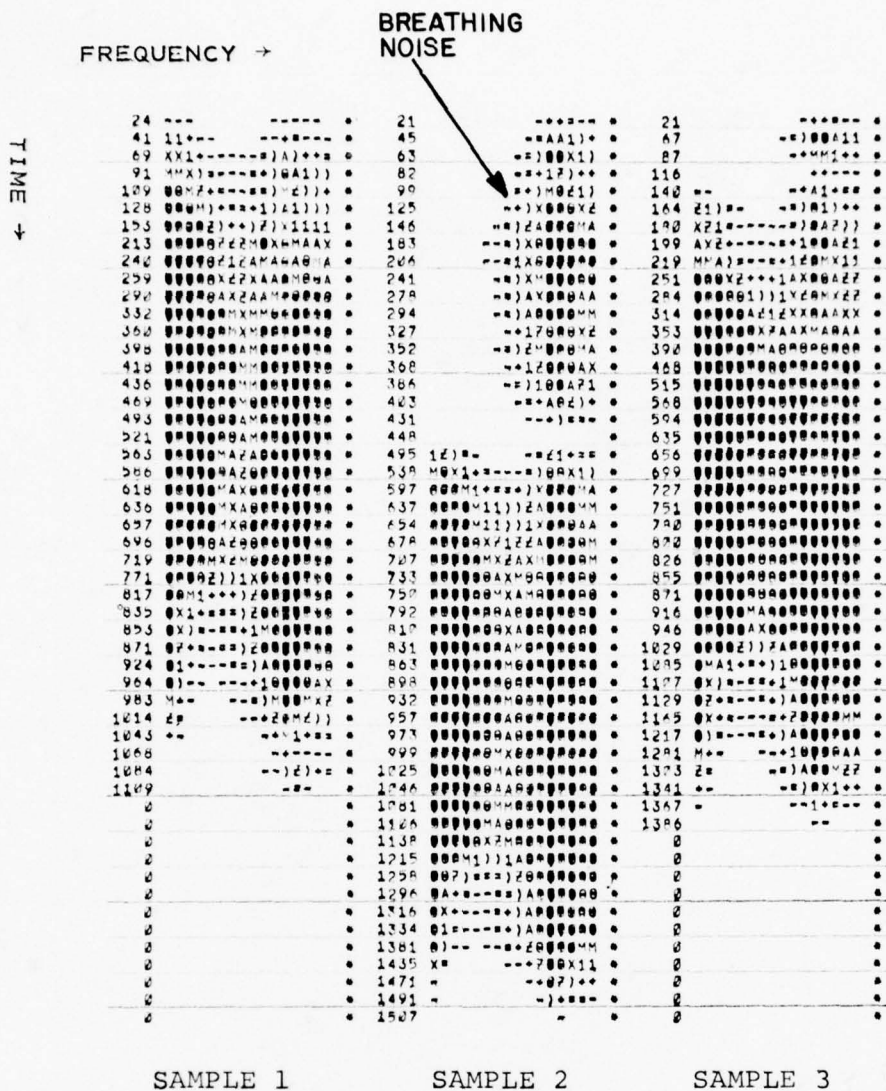


Figure 6. Spectrogram

To do this, samples of pure breathing noise were selected from several speech data files using DATED2. Similarly, samples of unvoiced fricatives from the words "six" and "seven" were selected. Averaged spectra for these samples were plotted and compared. Figure 7 shows such a plot. It was observed that both types of sound had energy predominately in the higher frequency filters. For the breathing noise, however, the energy peaked up in filters

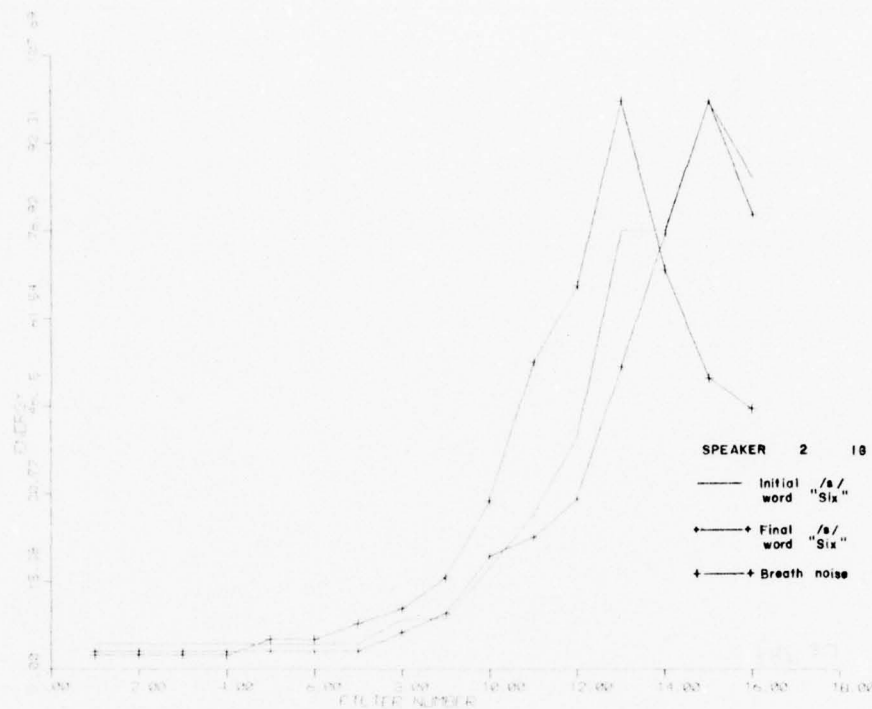


Figure 7. Averaged Spectra, Subject 2, 1g

12 or 13 while with the fricative sounds energy peaked up in filter 15. The following algorithm was devised as a test for each frame of data: eliminate the frame if

$$\sum_{j=1}^5 E_j < \frac{1}{TH} \sum_{j=12}^{16} E_j \quad \text{and} \quad \sum_{j=12}^{13} E_j > \sum_{j=15}^{16} E_j$$

where E_j is the energy in the j filter. This algorithm was embodied in preprocessing routine BNE1. When BNE1 was applied to the same files that manual editing had been applied to, the results of recognition experiments were within 1% of those obtained with the manual editing. The threshold TH was set to 10. The same algorithm was incorporated in the VDETS DSS and the results were favorable for most subjects to the extent that segments of breathing noise that triggered the word boundary light

and were accepted in the machine as words without the breathing noise eliminator were ignored by the machine with the breathing noise eliminator installed. On the other hand, in tests where breathing noise was not present, e.g. live input with the normally supplied microphone, the breathing noise elimination algorithm definitely impaired recognition performance.

Over the entire series of tests with the centrifuge data there were eight trials where all other processing parameters except the breathing noise eliminator were held constant. In these eight trials the recognition rate with the breathing noise eliminator was better in six cases, poorer in two. The average rates were 83.5% with the breathing noise eliminator and 80.3% without.

2.4.2 Alternate Word Boundary Test

In the normal VDETS algorithm each new frame of data is tested in the following way. The energy change between the new frame and the previous one, as defined by

$$\sum_{i=1}^{16} |E_{i,n} - E_{i,n-1}|$$

where $E_{i,n}$ is the energy in the i th filter for the n th time frame, is computed. If this change is greater than a threshold, the new sample is retrained; otherwise it is dropped. All of the data in the DEC-10 speech data files were originally processed with this algorithm. The new word boundary tested each sample by computing the following energy sum

$$\sum_{i=2}^{16} |E_i - E_{i-1}|$$

and rejecting the sample if this sum were below some threshold. This algorithm was embodied in the preprocessing routine BWBT. Over six trials where BWBT was applied or not applied and all other parameters kept the same, rates were better in five cases

with BWBT and poorer in only one. The average recognition rates were 80.7% with and 76.4% without.

2.4.3 Modification of Segmentation Routine

In the then current version of the VDETS algorithm, segmentation was accomplished by dividing the number of frames in the word by the number of segments, thus assigning equal numbers of frames to each segment. An alternate segmentation mode based on energy change as described in Appendix A was made available. Actually this segmentation algorithm was one that had originally been used in SEI voice recognition equipment but was abandoned in favor of the somewhat simpler divide-by-N process. In over 14 trials in which only the segmentation mode was varied, the energy change segmentation was better in nine cases, poorer in four cases, and equal in one case. The average recognition rates over these trials were 86.9 for the equal energy change segmentation and 85.9 for the divide-by-N mode.

2.4.4 Processing Mode

As described in Appendix A and Section 2.3 two modes of processing the raw data were available - the compress-before-coding, process mode 1 and the compress-after-coding, process mode 2. The data results showed these modes approximately equal. In 48 trials where only the process mode varied, mode 1 won 24 trials, mode 2 won 17 and there were 7 ties. The average rate was 78.2 for mode 1 and 80.8 for mode 2.

2.4.5 Modification of Coding

Considerable attention was paid to the algorithm by which the spectral data were reduced to a coded form. The coding algo-

rithms tested are described in Appendix A. Coding modes 1 through 4 were initially provided in the RESLT3 package.

Mode 4 was the mode employed in the then current VDETS process. The code is derived by comparing filter elements in a chain fashion, i.e. filter 1 versus filter 2, filter 2 versus filter 3, etc. Code mode 3 was a modification of this but in mode 3 the comparisons are made between independent pairs of spectral data. Filter 1 is compared with filter 2, filter 3 with filter 4, etc., to produce 8 elements of the code. The filters are combined in pairs and the sum of the outputs of filters 1 and 2 is compared with the sum of the outputs of 3 and 4, etc. to produce four more elements. The process is continued with filters summed together in groups of four and then eight to produce 15 elements in all.

The number of filter elements in the chain coding process of mode 4 is the same as in the independent coding process of mode 3. Note, however, that if the output of filter 2, for example, is greater than that of filter 1, then it is more likely that the output of filter 2 will be greater than that of filter 3 than it would have been if the output of 2 had been less than that of 1. Hence the elements of the code in the chain process are not statistically independent. The independent coding process therefore retains more information about the spectrum from which it was derived than the chain coding process and hence should be more effective in the speech recognition process.

In both modes 3 and 4 the code elements are binary and the coded representation of a spectral frame or segment requires only 15 bits. The training process produces a set of 15-bit coded segments for each reference pattern, but it also requires an equal number of bits to specify the masking function as discussed in Section 2.3.2. Since each element of the reference pattern requires 2 bits of storage, it seemed that a 3-level coding scheme

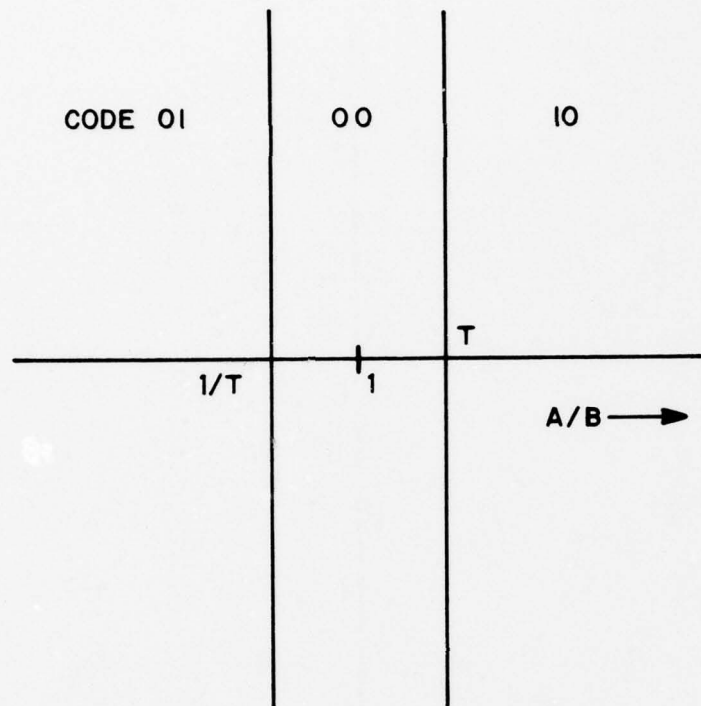


Figure 8. 3-Level Code Element

might be more effective than the binary one while requiring no more storage for the reference patterns.

In the 3-level scheme, spectral samples A and B are compared to produce a 3-level code element as shown in Figure 8. If the ratio A/B is greater than T , the coded output is 10, if the ratio is less than $1/T$ the output is 01; otherwise the output is 00.

The threshold can have any value, but the coding process is computationally simple if T is of the form $(2^n + 1)/(2^n - 1)$. In this case the coding requires only the comparisons A versus B and $2^n |A - B|$ versus $2^n |A + B|$. The only multiplication required is an n -bit left shift.

Three level coding modes 1 and 2 were implemented. Mode 1 employed independent comparisons analogous to mode 3 while mode 2 employed chain type comparisons as in mode 4. In both cases the threshold was $9/7$. Subsequently, mode 6 was added, being identical to mode 1 except that the threshold is $17/15$.

2.4.6 Feature Evaluation

The coding processes described so far produce patterns of 120 elements grouped into eight segments of 15 elements each. The training process is designed to eliminate from the reference pattern any of these elements that are inconsistent over the training set and hence presumed to be of relatively little value in the recognition process. A study was undertaken to investigate further the relative value of the elements in the code. It seemed likely that not all of the elements were of equal usefulness in the word recognition process and possible that the useful ones might vary with the g -level.

To carry out this investigation a routine, CODEST, was developed. This routine compares a set of test utterances with a set of

reference patterns and determines the rates of occurrences of hamming distances zero, one and two for both in-class and out-of-class comparisons. The data are averaged over all segments of the word patterns. The results then are estimates of the probabilities for obtaining hamming distances of zero, one or two for each of the 15 elements of the code for in-class and out-of-class reference patterns. A good feature for the recognition process would be one with a high probability of zero hamming distance in-class and a low probability of zero hamming distance out-of-class. A measure of this type of effectiveness is the Battacharyya distance¹ defined in the general case by

$$B(S_1, S_2) = -\ln \int_{-\infty}^{\infty} [P(x|S_1)P(x|S_2)]^{\frac{1}{2}} dx$$

where S_1 and S_2 are classes and $P(x|S_i)$ is the conditional probability density of obtaining feature x when the sample belongs to class i . For the speech tape data the Battacharyya distance takes the form

$$B = -\ln \sum_{i=0}^2 [P_{in}(i)P_{out}(i)]^{\frac{1}{2}}$$

where $P_{in}(i)$ is the probability of obtaining a hamming distance of i for an in-class comparison and $P_{out}(i)$ is the similar probability for an out-of-class comparison.

Measurements were made for several speakers from the centrifuge experiments and from live inputs. The study revealed that some elements were much better than others and that some were almost worthless (B approaching zero). There was generally good agreement in the poorer elements over all speakers and at all g -levels. A scoring mode (mode 3) was added that permitted weighting the code elements unequally. Several tests were made with this approach and with various weight assignments. This approach to taking advantage of the relative efficacy of the various elements was abandoned in favor of the approach described below.

It was found that the code elements that result from the comparison of filters 13 with 14 and filter 15 with 16 had generally small Battacharyya distances while the code elements resulting from the comparison of filters 1+2 with 3+4 and 5+6 with 7+8 had relatively large Battacharyya distances. Accordingly a code mode 9 was added to the repertoire in which the two elements with low Battacharyya distances were replaced with elements obtained by comparing filters 2+3 with 4+5 and 3+4 with 5+6. Also, since a sixteenth code element is available free, as it were, since the system runs on a 16 bit machine, an additional element obtained from comparison of filter 4+5 with 6+7 was added in the sixteenth position. Code mode 9 is otherwise the same as mode 1, i.e. it uses 3 level comparison with a threshold of 9/7. Code mode 10 was also added, being the same as mode 9 except with a 17/15 threshold.

2.4.7 Evaluation of Coding Modes

An evaluation of the relative effectiveness of coding modes 1 through 4, 6, 9 and 10 was made in the following manner. From all of the recognition experiments run, sets were selected where only the coding mode varied, all other parameters being held constant. The selection of such sets was comprehensive. From these sets, subsets were selected for each coding mode.

The result was a series of trials for each mode with that mode pitted against one of the other modes in an equal contest, i.e. one where all other parameters were the same. For each mode a score was tallied of the number of these contests won, lost and tied. Also, the average recognition rate for the mode in question versus that for the other modes in these contests was calculated. The results are shown in Appendix B. The independent coding modes 1 and 3 are clearly better than the chain coding modes 2 and 4. The three level coding seems somewhat better than the two level although the results are not conclusive. Mode 2,

which is three level chain type, coding was the poorest of all. Modes 1 and 6 where the only difference is the comparison threshold, 9/7 versus 17/15, had approximately equal records, but between modes 9 and 10 where again the only difference is the comparison threshold, mode 10 was clearly superior. Mode 10, in fact, has the best performance by far.

2.4.8 Other Coding Modes

Several other coding algorithms were tried with results that seem to be significant to the general speech recognition problem. All of the coding modes described so far produce outputs that are sensitive to spectral slopes, through comparison of the energy in adjacent sections of the speech power density spectrum. Other types of coding, not based on slopes, were tried. In these modes the code elements were derived by comparing the filter output in each spectral frame with the average filter output over the utterance. Several variations were tried. With the processing mode 2, i.e. code-before-compress, it was possible to calculate the average spectrum over the utterance and then to go back and use this in the coding process. Each element of the code, then, was generated by comparing a filter output for the frame with the average output of that filter for that utterance. Two level and three level codes were tested. Where processing mode 1 was used the average spectrum was normalized as was the average spectrum for each segment before applying the coding process. Both peak normalizing and average normalizing were tried.

These coding techniques are sensitive to spectral shape but are almost completely insensitive to spectral slopes. In all cases tested the recognition performance was quite poor in comparison with the slope sensitive coding modes. Differential rates of 20 to 25% were common.

2.4.9 Inverse Filtering

Recognition tests with the available repertoire of processing modes revealed a marked degradation in the capability of any of the algorithms with increasing g-level. For example Appendix B shows typical recognition rates for subject 2 at 1g, 3g and 5g. An investigation was made to determine why this was so, and if there were any characteristic changes in the speech pattern with g-level.

The general method employed in the investigation was the comparison of spectral plots at the various g-levels. One approach was to average the response characteristic over one repetition of the word list. Figures 9 through 14 illustrate the results for several subjects. In each case the composite spectra at 1g, 3g and 5g are plotted. For comparison Figure 15 shows the composite spectra for 3 separated repetitions of the word list at 1g for subject 2. (The spectra were peak normalized in all cases.) While there is a marked change in the spectral characteristics at different g levels for all subjects, there is no apparent pattern to these changes. In most cases, the upper peak in the spectrum seemed to shift down by at least one filter from 1g to 3g and 5g. For subject 6, however, the reverse occurred and the upper peak shifted upward for the higher g-levels. For subject 5 the peak occurred at the same place at all three levels. The relative amplitude of the peak in the lower end of the spectrum varied considerably with g-level although the peak itself generally remained in the same filter for a given subject. Again there was no consistency in the direction of the changes.

Another approach was to compare the compressed word pattern for individual utterances at different g-levels. Figures 16 through 20 illustrate the results. These plots show the spectral response versus filter number for each of the eight segments. The words are processed by segmentation mode 2 and processing mode 1. Figures 16 and 17 are two repetitions of the word "four" for

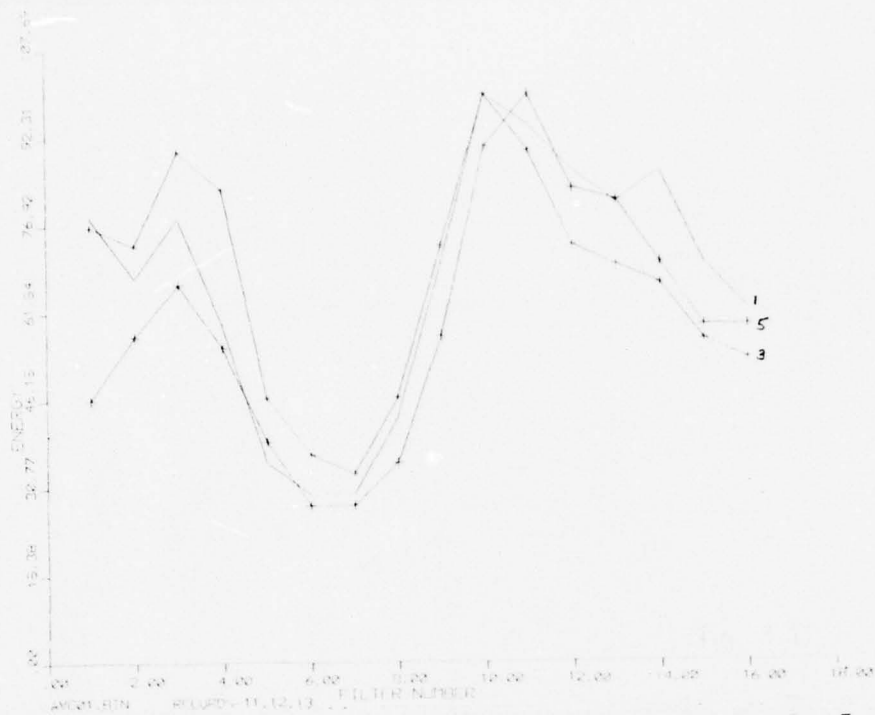


Figure 9. Averaged Spectra; Subject 1; 1, 3, 5g

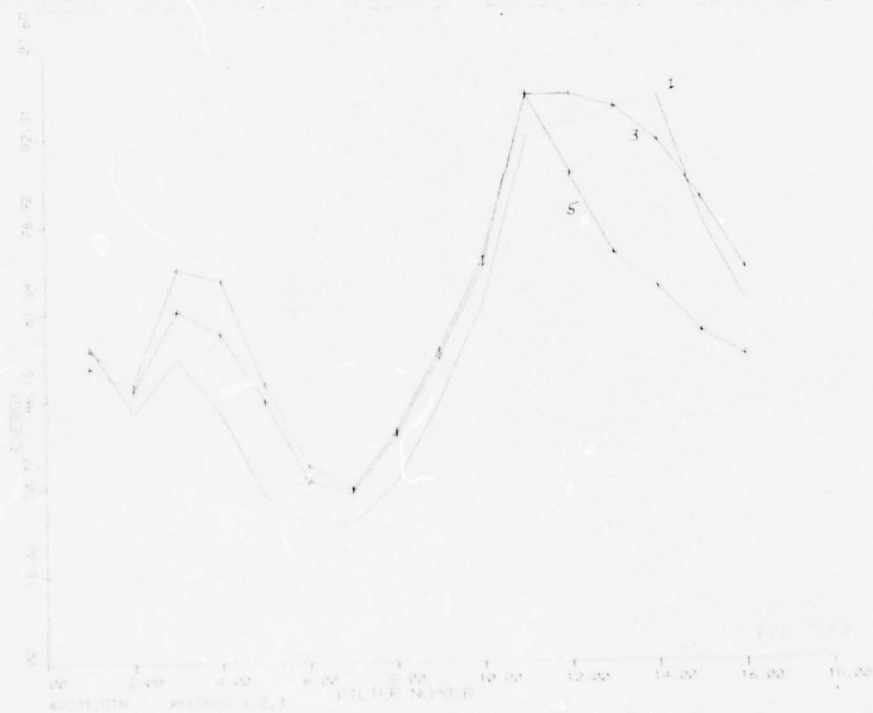


Figure 10. Averaged Spectra; Subject 2; 1, 3, 5g

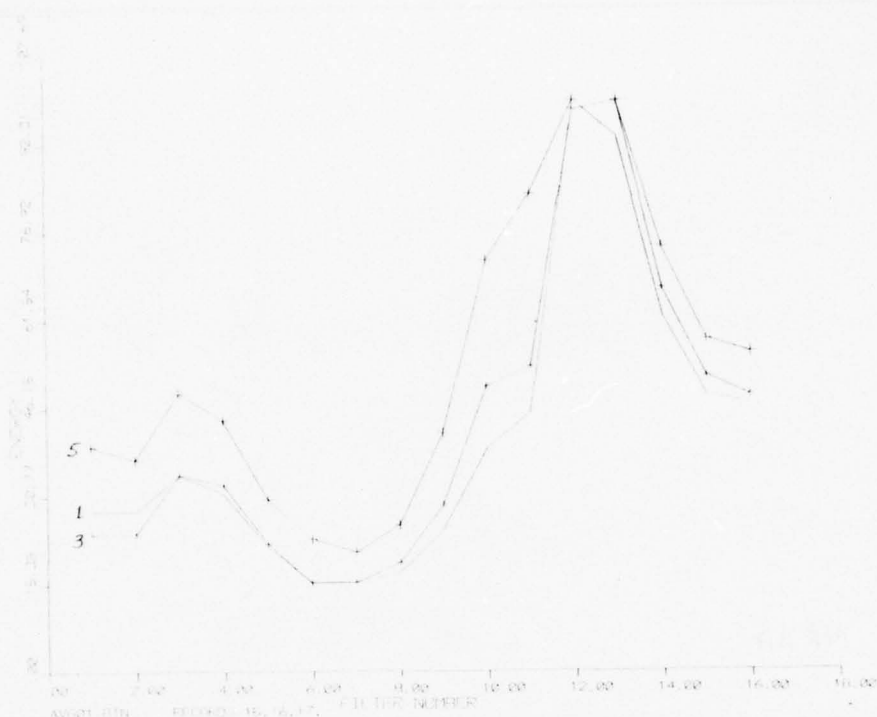


Figure 11. Averaged Spectra; Subject 3; 1, 3, 5g

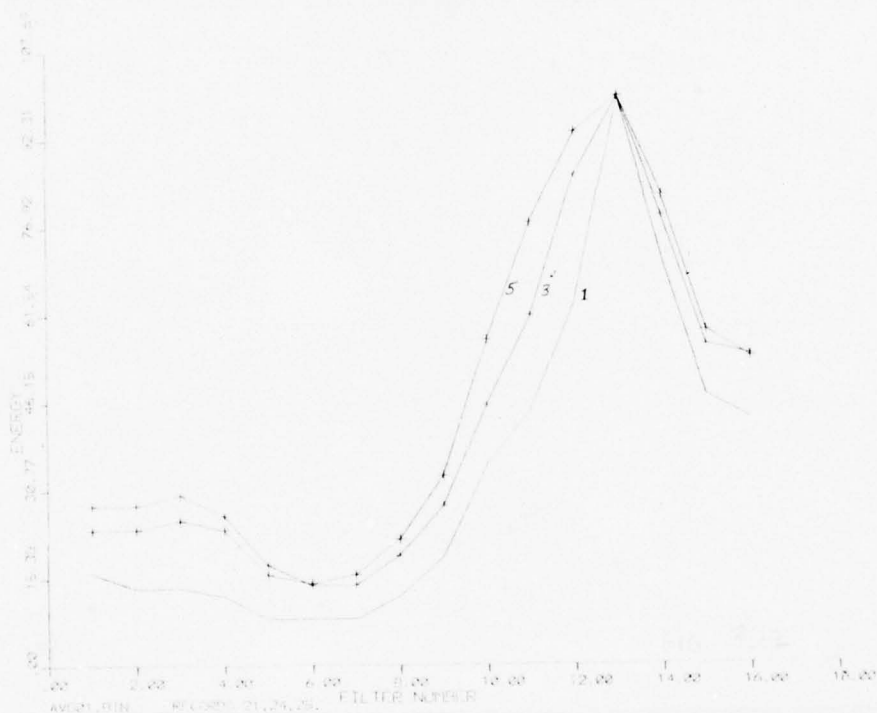


Figure 12. Averaged Spectra; Subject 5; 1, 3, 5g

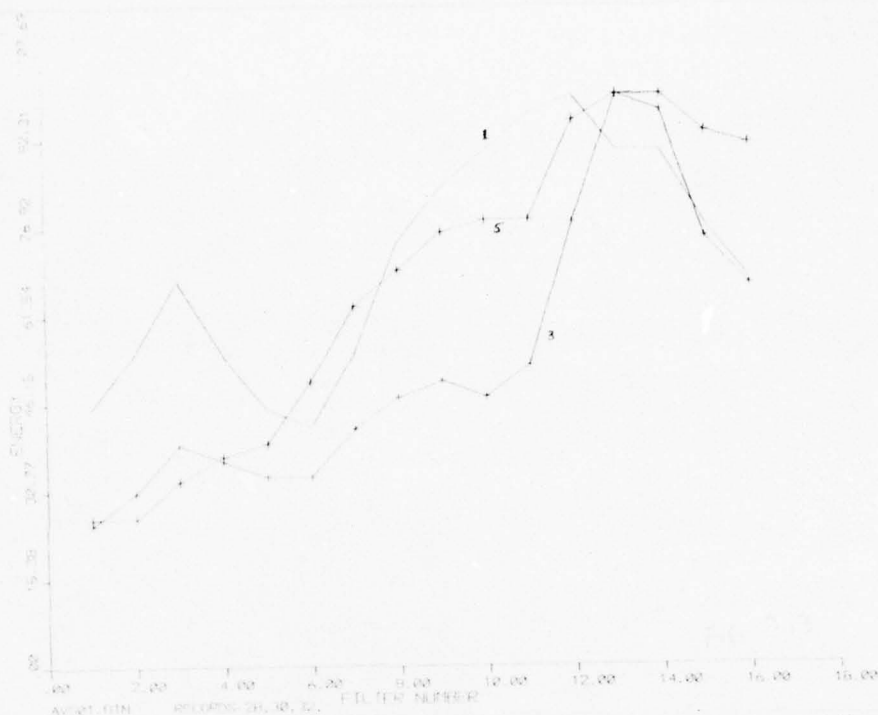


Figure 13. Averaged Spectra; Subject 6; 1, 3, 5g

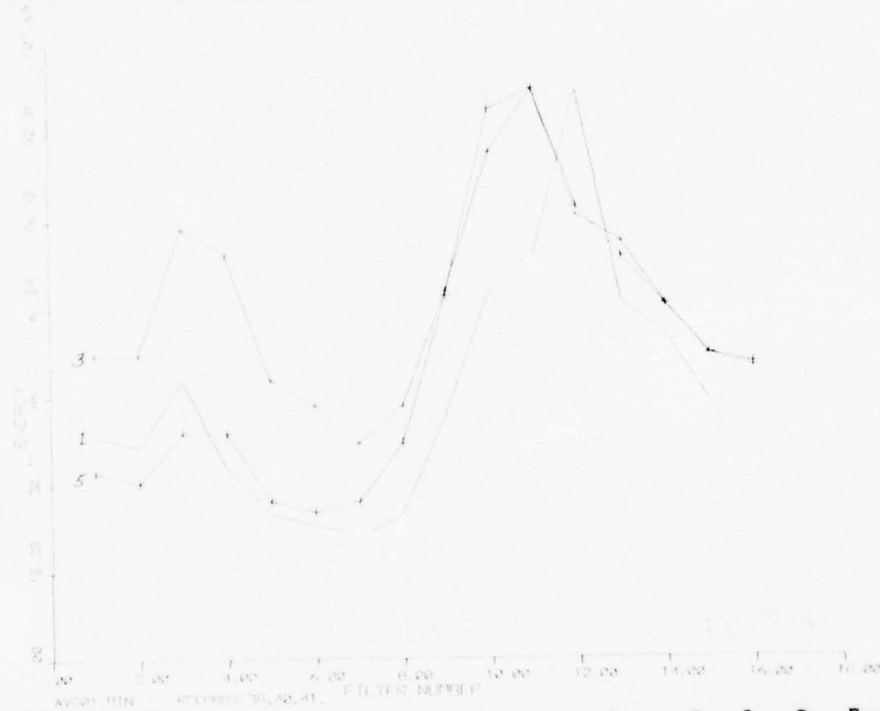


Figure 14. Averaged Spectra; Subject 8; 1, 3, 5g

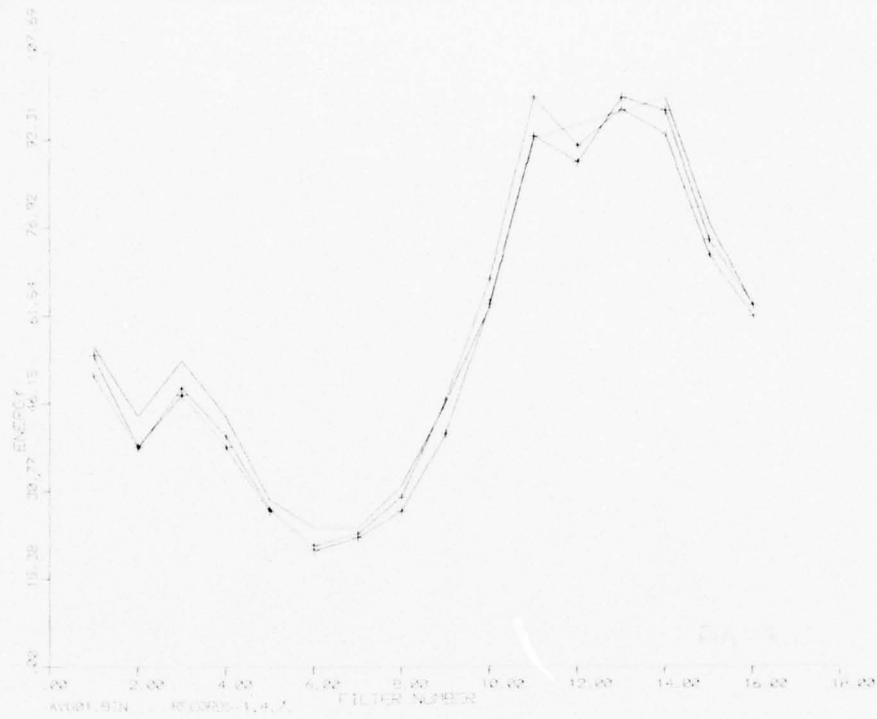
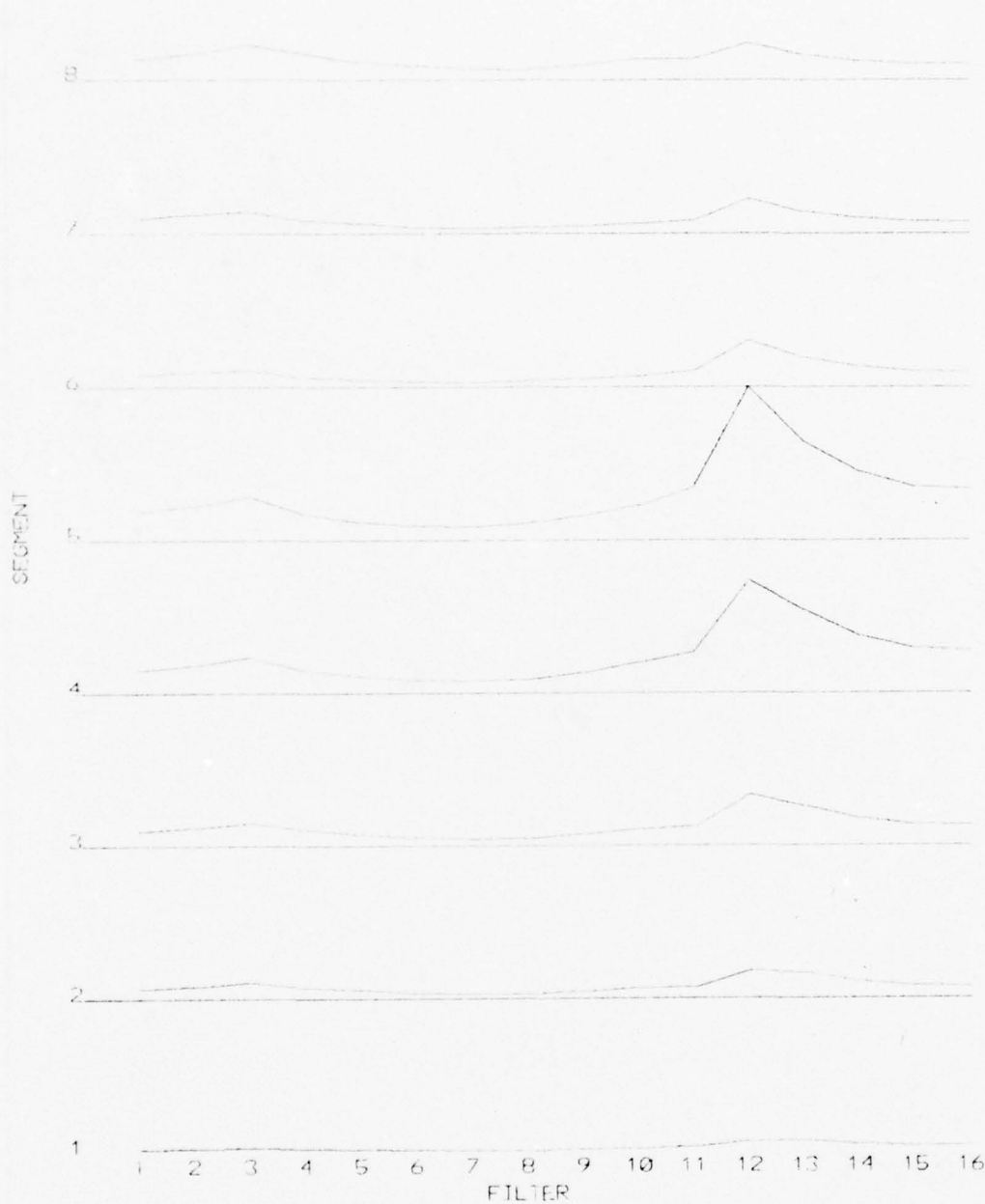


Figure 15. Averaged Spectra; Subject 2; 1g



W-4. S-1

Figure 16. Spectral Response vs Filter No., "Four," 1g, Repetition 1



W-4, S-2

Figure 17. Spectral Response vs Filter No., "Four," lg, Repetition 2



W-4, S-11

Figure 18. Spectral Response vs Filter No., "Four," 5g

subject 3 at 1g. Figure 18 is one repetition of the same word at 5g. Note the shift and broadening of the higher frequency peak segments 6, 7 and 8 at 5g. Figures 19 and 20 show the word "eight" at 1g and 5g respectively. Note the down shift of the upper peak through most of the segments.

Similar curves were plotted for other words and subjects with similar results. The patterns were more consistent at 1g than at the high g levels and at the high g levels there were changes in the patterns marked by broadening and shifting of peaks.

A tentative explanation for the variation of the spectral characteristics of the speech samples with g-level follows. The mechanism for the production of speech sounds can be represented as shown in Figure 21. A signal source supplies either pulsed or noise like signals to a filter structure consisting of the oral or nasal cavities. In the frequency domain we may represent the spectrum of the source as $S(\omega)$ and that of the vocal cavities as $H(\omega)$. Both S and H are varied by the speaker in producing different sounds. Where the speech is to be processed electronically and specifically in the word recognition device we must add a third characteristic $G(\omega)$ in the chain, where G is the spectral response of the microphone and the amplifier circuits used. The spectral response measured is the product of the three functions, $S(\omega)$, $H(\omega)$, and $G(\omega)$.

In most word recognition applications S and H vary characteristically with the words spoken while G remains constant. Any variation of G that significantly modifies the spectral characteristic might be expected to have an adverse effect on the word recognition process. In the centrifuge experiments a mechanism exists for the variation of G with g-level. All of the data were taken with the subject wearing a face mask with a built-in

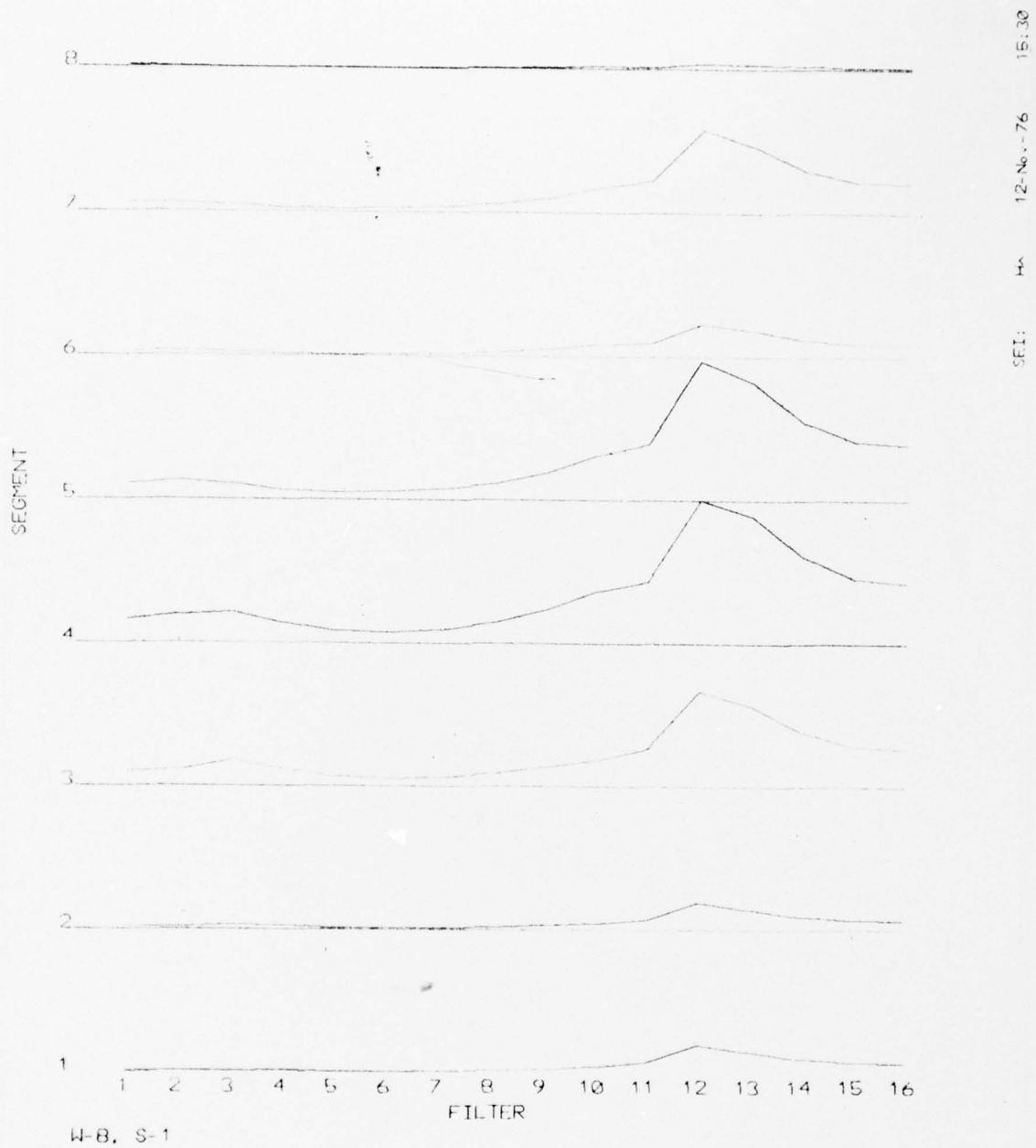


Figure 19. Spectral Response vs Filter No., "Eight," 1g

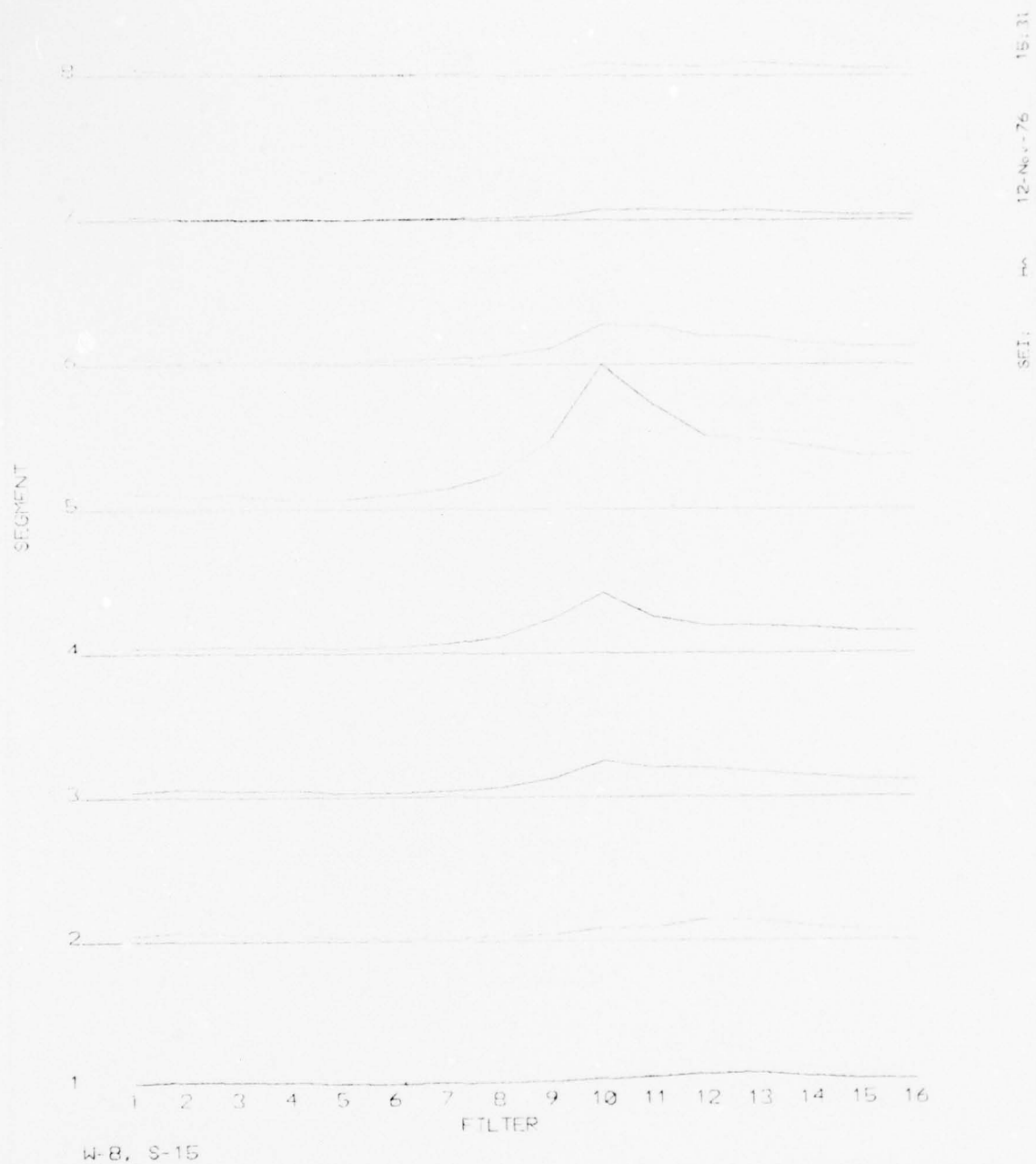


Figure 20. Spectral Response vs Filter No., "Eight," 5g

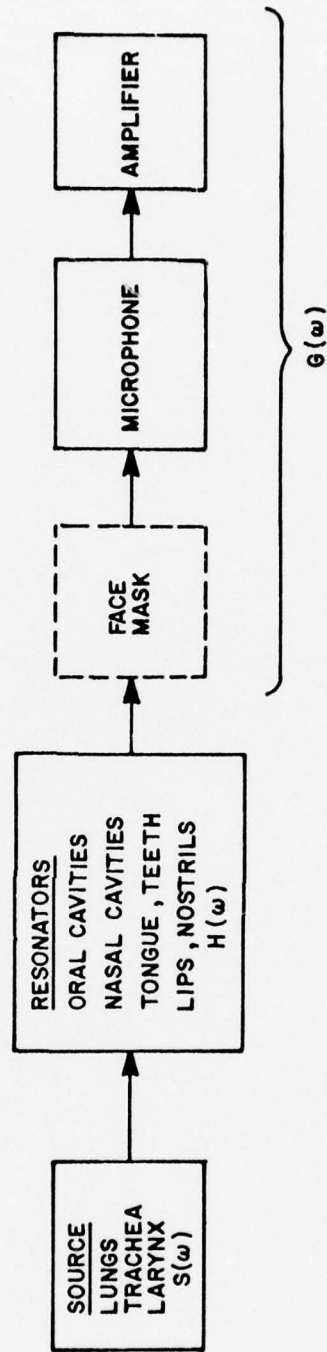


Figure 21. Mechanism for Production of Speech Sounds

microphone. The mask fits tightly around the nose and mouth and creates a resonant cavity that will significantly modify the spectral characteristics of the speaker's voice.

Now if the mask remains stationary, then the function $G(\omega)$, although significantly different from that which would have been obtained without the mask, at least remains fixed, and hence does not interfere with the recognition process. There are two mechanisms that could cause a change in the response function introduced by the mask, however. First, if the mask is removed and then replaced it may be put in a somewhat different position; and second, the effect of g-force stress can cause the mask to slip or can otherwise distort its shape. Both of these mechanisms were present. In most cases the subject put the mask on and left it in position through the training passes and the first lg run. In most cases after the g-force runs, the mask had either slipped or had become uncomfortable and the subject had to readjust it. In many cases he removed the mask and later replaced it.

If we knew what the function $G(\omega)$ was we could eliminate the effects of its changing by multiplying the composite characteristic by the inverse $1/G(\omega)$. We do not know and have no way of measuring G and its changes. We can, however, average the response over one or more repetitions of the word list to obtain the average response

$$W = \overline{S(\omega)} \overline{H(\omega)} \overline{G(\omega)}$$

where $\overline{\quad}$ denotes the average. If the average is made over conditions, i.e. constant g-level, where $G(\omega)$ might be expected to remain constant, then we may remove the bar from over $G(\omega)$.

If we then use the inverse of W to filter the instantaneous spectral response we have the modified spectral function for the speech data

$$\frac{S(\omega) H(\omega)}{\bar{S}(\omega) \bar{H}(\omega)}$$

This function may or may not be as good as the original function for recognition purposes, but at least the effects of variation of the reproduction channel have been removed.

A preprocessing routine SPEQ was written to apply the inverse filtering described above to speech data files. SPEQ goes through the file and takes the first occurrence of each word in the vocabulary and computes the spectral average over this set of utterances. The routine then multiplies all spectral data in the entire file by the inverse of the average spectrum thus computed.

A variant of this was the routine SPEQA. Here the average spectrum is computed as in SPEQ over the set of first utterances of all words in the vocabulary. SPEQA then goes back and applies the inverse filter to all spectra also, as in SPEQ. The average spectrum of the word just processed is the ratio of $(1/8):(7/8)$ for the new and old spectra respectively.

Results for the inverse filtering process were significant. In 63 trials where recognition performance with either SPEQ or SPEQA was compared with performance without either of these being applied but with all other parameters identical, recognition was better with inverse filtering in 45 cases, poorer in 11, and equal in 7. The mean rates were 75.6% with inverse filtering and 70.3% without. In 30 trials, at higher g -levels, i.e. greater than 1, inverse filtering produced better recognition in 23 cases, poorer in only 1, with 6 ties. The mean rates were 64.2% with filtering and 57.6% without. In cases where SPEQ

and SPEQA were both applied, their effectiveness was about equal. These data are presented in somewhat different form in the bar chart of Figure 22.

It is obvious from the recognition rates quoted above that inverse filtering is not the panacea that will make the recognition performance under g-force stress with a face mask equal to that obtainable under normal conditions. There are several possible reasons why this is not so. First the spectral function $S(\omega) H(\omega) / \overline{S(\omega) H(\omega)}$ simply may not be as good as the unmodified function for the recognition purposes. Second, the assumption that $G(\omega)$ remains constant over a test run at a particular g-level may not be valid in that the mask might slip or move suddenly at any time during the run. Finally, it may be that modification of the system response function caused by changes in the shape or position of the face mask is not the whole story. Certainly in the process of "getting on top," the subject exerts some effort and becomes somewhat winded. In almost all cases the second lg run showed significantly poorer recognition rates than the first one. This run was usually made immediately after the 5g run while the subject was resting. He was usually winded at the beginning of this run, in addition to having possibly removed and replaced the face mask. It might be expected under these conditions that more errors might be made during the first part of the second lg run and during the later parts in that the subject was regaining his breath during the whole period. No such effect was observed.

2.4.10 Multimode Training

The original training procedure is described in Section 2.1. During this procedure only one reference pattern is maintained for each word of the vocabulary. For each new sample this reference pattern is modified only by modifying the masking function to reflect any new nonconsistent elements. This mode

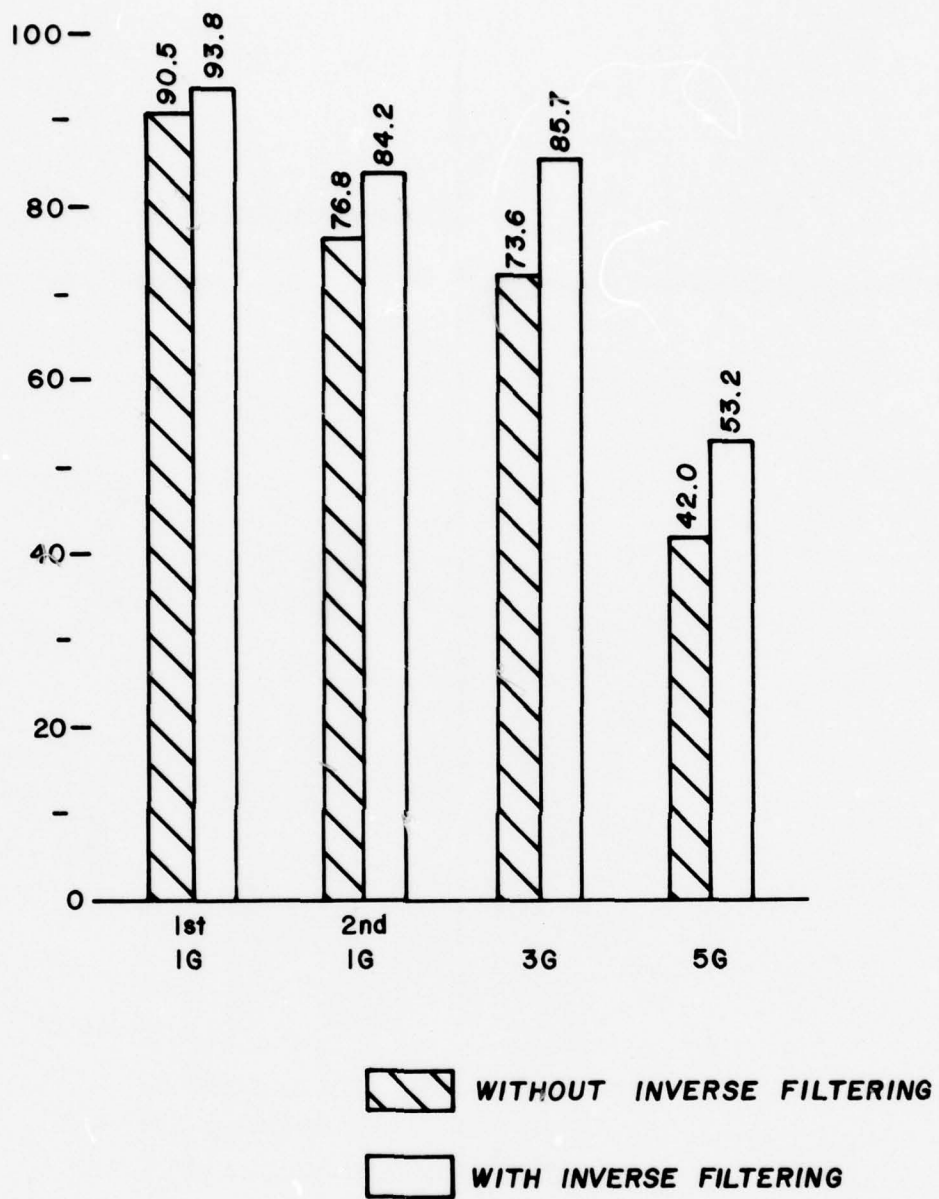


Figure 22. Recognition Performance With and Without Inverse Filtering

2

of training is normally satisfactory for word recognition applications. It does have the weakness, however, that a bad sample can cause the masking of an undue number of elements in the reference pattern for a single word. Even without bad samples, however, words may be spoken in more than one mode and all modes get lumped together in a single reference pattern.

A scheme for multimode training, i.e. where each vocabulary word may have more than one reference pattern, was implemented. The process operates as follows. The coded versions of all samples of all words in the training set are maintained in storage until the hamming distance matrix is computed. This matrix contains the distance between each sample and every other sample. A threshold distance is set and the training samples are grouped together such that the hamming distances between all members of the set are less than or equal to the threshold distance. Enough sets are chosen so that each sample is represented in at least one set. Some samples may appear in more than one set, however. Once the numbers of the training set have been placed into subsets within the threshold distance, then the training procedure for each subset is carried out as before.

A reference pattern is generated with all nonconsistent elements masked out. Note that if the threshold distance is made larger than the hamming distance could possibly be, then all of the training samples will be lumped together in the original single-mode process.

Multimode training was found to be effective. The parameter RPD (reference pattern distance) is the threshold value. A value of 50 or 60 for this parameter was found to be effective for multimode training. For single mode training, the value for RPD is noted as INF. In 30 trials where RPD = INF was compared with RPD = 50 or 60 and all other parameters remain fixed, the multimode training provided an average recognition rate of 85.5 versus

80.8 for the single mode training cases. Of the 30 trials the recognition rate was better in 18 with multimode, better in only 3 cases with single mode, and there were 9 ties.

2.4.11 Time Warp Comparison

At the beginning of the program it was believed that considerable benefit to the recognition process might be achieved by the use of a time warp comparison of the unknown speech pattern with the reference pattern. Such techniques have been successfully used by others (accordingly, software was developed to implement the time warp comparison by dynamic programming as described by Itakura².) Listings of the routines involved are contained with the software package under the title "FPATH."

Although FPATH is applicable to a range of $M \times N$ element comparisons, it has been used on this program only for comparison of 8 segment unknowns with 8 segment reference patterns. Time warp comparison is implemented in COMP mode 1 of RESLT3. When this mode is selected, the time warp comparison is invoked both for training and recognition.

In the training mode the time-warp algorithm is used to align the reference pattern with each new sample going into the training base. The comparison is done so that each segment of the reference pattern is used while some segments of the new training sample may be used more than once and others not used. Only if the optimum path turns out to be straight will all segments of the new sample be used once and only once. Once the order of comparison has been established, then the elements of the code are compared for matching segments of the reference and the new samples, and inconsistent segments of the reference pattern are masked as in normal training. In the recognition mode the time-warp algorithm is used to find the minimum distance path and the corresponding distance is used in computing the score.

Results with the time-warp algorithm were disappointing. In nine trials where it was compared with the straight comparison mode, it provided a better recognition rate in only one case and there the difference was less than 1%. In other trials the straight comparison mode produced better results by 3% to 5%. Further tests with the time-warp mode were abandoned.

2.4.12 Summary of Results

A table with comprehensive listing of the results of all the recognition experiments performed on the DEC-10 system is given in Appendix B. The records in this table are sorted by subject number, g-force level for the recognition file, the file from which training data were taken, the number of samples and sequence numbers of the training data, and the recognition rate.

Table III lists the best recognition scores obtained for all subjects by g-level. Also shown are the results obtained with the original algorithm, i.e. the VDETS algorithm used in the machine at the time the data were taken. This table indicates the progress made in improving the algorithm for recognition under g-force stress. The bar chart of Figure 23 summarizes the performance versus g-level over all subjects.

TABLE III. BEST RATES AND ORIGINAL RATES

	1G		3G		5G		2nd 1G		7G	
	ORIG	BEST	ORIG	BEST	ORIG	BEST	ORIG	BEST	ORIG	BEST
1	83.7	91.8	-	94.6	47.0	56.6	71.6	84.2		40
2	89	100	64.6	93.7	65.8	88.6	70.5	91.0		
3	-	92.1	-	80.8	-	41.8	-	69.7		33
4	78.1	90.4	38.0	79.8	25.0	51.6		-		
5	-	100	-	96.4	-	75.9	-	88.2		100
6	98	100		79.3		38.9		90.2		
7	-	95.6	-	98.7	-		-	98.0		
8	-	85.5	-	81.7	-	31.8	-	76.3		
9	72.6	88.7	53.7	73.2	12.7	36.7	38.6	54.2		

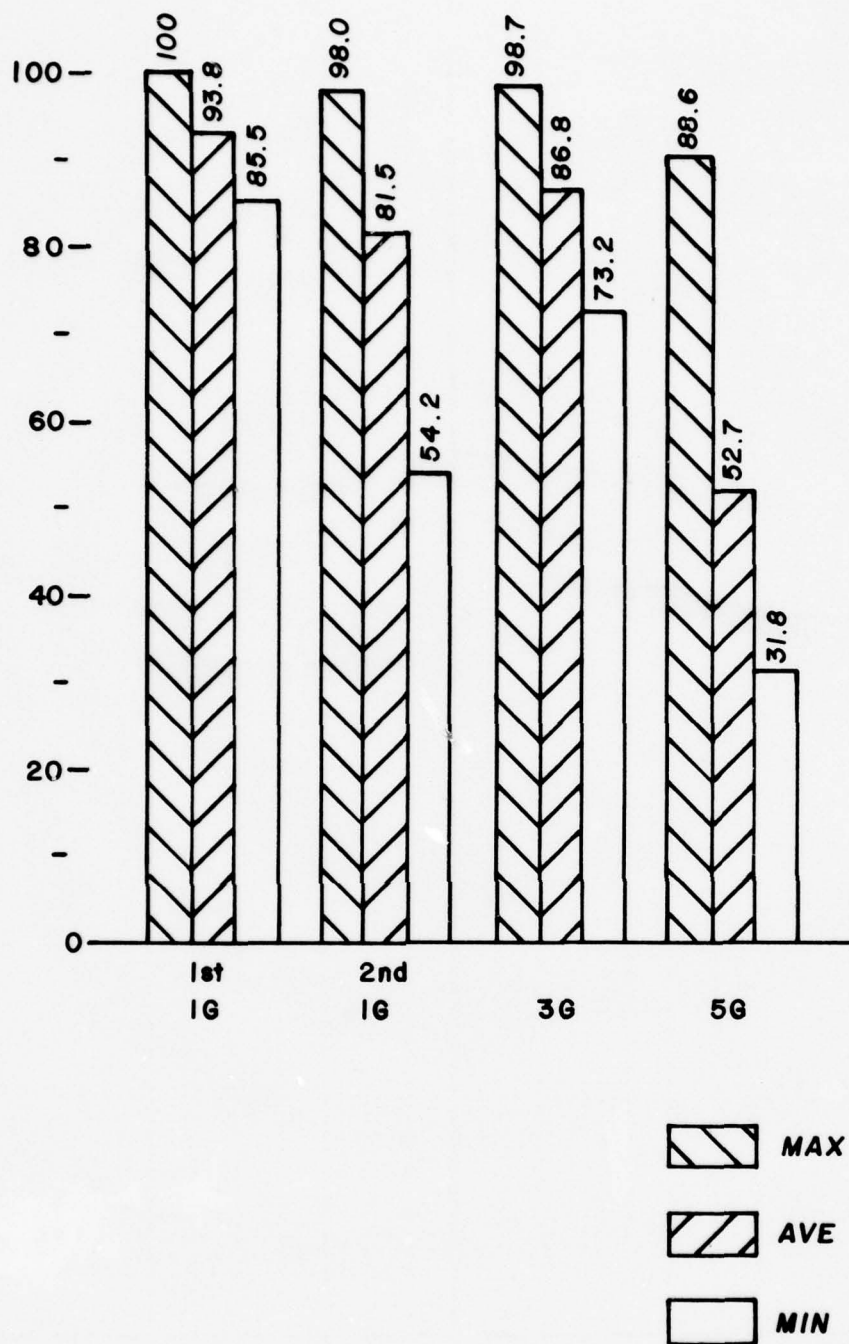


Figure 23. Performance vs g-Level for All Subjects

3. CONCLUSIONS

The objectives of this program were to investigate the effects of g-force stress on the subjects' vocal patterns as applicable to the word recognition process in isolated word recognition systems, and to find a means for making such a system work under the adverse conditions of g-force stress. The investigators were not certain at the outset that g-force stress would cause any significant difference in the voice pattern or in the ability of a word recognition device to function with acceptable accuracy. Any doubts on this score were soon dispelled after the initial results from data taken on the human centrifuge at the Brooks Air Force Base were observed. Recognition rates as shown in Table III were well below the acceptable level of 98% and decreased with increasing g-force stress. The rates, however, were below the acceptable level even for the nonstress, i.e. 1g, case. This indicated that something more than g-force stress was at work.

Through a number of experiments on the data, testing various modifications of the recognition process, it was found to be possible to improve the recognition performance, in many cases markedly. Modest improvements were obtained by modifying the word segmentation and coding process. Significant improvements were obtained by the use of a multi-mode training process, inverse filtering and breath noise elimination as shown in Table IV. With these measures it was possible for some subjects to bring the recognition rates at 1g and 3g up to an acceptable level. A general solution, however, was not found.

It may certainly be concluded that putting on a face mask and riding in a centrifuge at g-force levels of 3g and higher causes modifications in human voice patterns. These modifications had an adverse effect on the capability of the SEI VDETS word recognition device and would undoubtedly have similar effects on other

word recognition machines. There is strong evidence that the face mask is largely responsible for the voice pattern variations with g-force stress. The face mask interposes a frequency dependent characteristic in the transmission path. This characteristic varies with the positioning and shape of the mask, both of which can change with g-force stress. Inverse filtering is partially successful in counteracting the effects of the mask.

TABLE IV. RECOGNITION RATE IMPROVEMENTS

<u>Process</u>	<u>Average % Improvement</u>
Breath Noise Eliminator	3.2
Inverse Filtering	
(1, 3 & 5 g-levels)	5.3
(3 & 5 g-levels)	6.6
Multimode Training	4.7

We believe that the key to successful operation of voice recognition devices in the cockpits of fighter aircraft is the elimination of the effects of the face mask. Accordingly, for continuation of the investigation, we recommend that this be given primary attention. It would be possible to eliminate the face mask entirely by means of some device such as a throat microphone. Also it might be possible to redesign the mask in some way so that it has less effect on the acoustic transmission path. From a practical standpoint, neither of these solutions is applicable; some processing technique must be found to eliminate the effects of the mask from the signal.

The inverse filtering process investigated in this program was a crude attempt to eliminate face mask effects. It was partially successful, but a more sophisticated approach is required. Some form of inverse filtering is a possibility. Another possibility is to determine those portions of the spectrum most affected by the face mask and eliminate them from the recognition process.

Finally it has been demonstrated that the reflection coefficients derived from LPC analysis can be applied directly to model the vocal tract.^{3,4} The face mask cavity can be considered as an extension of the vocal tract, and the speech signal can be represented in terms of reflection coefficients. It is possible, therefore, that such a representation can be used for recognition purposes and that the face mask effects can readily be eliminated by separating out those coefficients associated with the portion of the extended vocal tract represented by the mask.

4. REFERENCES

1. Andrews, H.C., Introduction to Mathematical Techniques in Pattern Recognition, p. 37, Wiley-Interscience, New York 1972.
2. Itakura, F., "Minimum Prediction Residual Algorithm Applied to Speech Recognition," IEEE Trans. Acoust., Speech and Signal Processing, Vol ASSP-24, pp. 67-72, Feb. 1975.
3. Wakita, H., "Direct Estimation of Vocal Tract Shape by Inverse Filtering of Acoustic Speech Waveforms," IEEE Trans. Audio and Electroacoustics, Vol AU-21, N5, pp. 417-427, Oct. 1973.
4. Wakita, H. and Gray, A.N. Jr., "Numerical Determination of the Lip Impedance and Vocal Tract Area Functions," IEEE Trans. Acoust., Speech and Signal Processing, Vol ASSP-23, pp. 574-580, Dec. 1975.

Appendix A

RESLT3 DESCRIPTION AND INSTRUCTIONS

RESULTS DESCRIPTION AND INSTRUCTIONS

INTRODUCTION

RESULTS IS A ROUTINE TO PERFORM SPEECH TRAINING AND RECOGNITION EXPERIMENTS. THERE ARE THREE BASIC MODES: TRAIN ONLY, RECOGNIZE ONLY AND TRAIN AND RECOGNIZE. TRAINING INPUT CAN BE TAKEN FROM ONE FILE AND RECOGNITION DATA FROM ANOTHER, ALTERNATELY THE SAME FILE CAN BE USED FOR BOTH TRAINING AND RECOGNITION. IN THIS CASE TRAINING IS DONE ON THE DESIGNATED SAMPLES, AND ANY ADDITIONAL SAMPLES ARE USED FOR RECOGNITION. TRAINING SAMPLES ARE NOT USED FOR THE RECOGNITION EXPERIMENT.

DATA SOURCES

THE ROUTINE ACCEPTS DATA FROM SPECIAL FILES GENERATED BY ROUTINES TO TRANSMIT DATA FROM THE VDETS DSS TO THE DEC-10. THESE FILES HAVE ALTERNATING DATA AND LABEL RECORDS WITH THE LABEL FOLLOWING THE DATA. BOTH ARE PACKED FOUR BYTES TO A DEC-10 WORD. THE DATA FILES ARE OF VARIABLE LENGTH UP TO 768 WORDS AND CONTAIN THE RAW DATA FROM A SINGLE UTTERANCE AS GATHERED BY THE VDETS. AFTER UNPACKING THE DATA RECORDS CONTAIN UP TO 3272 WORDS IN A 16XN ARRAY WHERE EACH 16-ELEMENT VECTOR IS A SPECTRAL SAMPLE, AND N IS THE NUMBER OF SAMPLES IN THE PARTICULAR UTTERANCE. THE LABEL RECORD IS A SINGLE WORD THAT UNPACKS TO FOUR WORDS WITH THE FOLLOWING SIGNIFICANCE: WORD 1-UNASSIGNED, WORD 2-SEQUENCE NUMBER OF TRANSMISSION, WORD 3-VOCABULARY WORD NUMBER, AND WORD 4-THE NUMBER OF SPECTRAL SAMPLES IN THE DATA RECORD.

OPTIONS

OPTIONS EXIST FOR THE FOLLOWING PARAMETERS: PROCESSING MODE, SEGMENTATION MODE, CODE MODE, COMPARISON MODE, THE REFERENCE PATTERN DISTANCE AND THE SCORING MODE. A DISCUSSION OF THESE OPTIONS FOLLOWS:

PROCESSING MODE

TWO OPTIONS EXIST FOR THE PROCESSING MODE:

- 1-CODE AFTER COMPRESS
- 2-CODE BEFORE COMPRESS

IN MODE 1 THE COMPRESSED DATA IS DERIVED BY SUMMING SPECTRAL SAMPLES OVER EACH SEGMENT. THE COMPRESSED SPECTRUM FOR EACH SEGMENT IS USED FOR THE INPUT TO THE CODING ALGORITHM. IN MODE 2 EACH RAW DATA SAMPLE IS CODED INDEPENDENTLY. COMPRESSION IS DONE BY COMBINING THE CODED SAMPLES OVER EACH SEGMENT. IN THIS CASE THE COMPRESSION IS DONE BY SUBROUTINE COMP2.

SEGMENTATION MODE

THREE OPTIONS EXIST FOR THE SEGMENTATION MODE:

- 1-EQUAL NUMBER SEGMENTS
- 2-EQUAL ENERGY CHANGE SEGMENTS
- 3-EQUAL LOG(ENERGY) CHANGE SEGMENTS

IN MODE ONE THE RAW DATA IS DIVIDED INTO SEGMENTS BY DIVIDING THE TOTAL NUMBER OF SAMPLES IN THE UTTERANCE BY THE NUMBER OF SEGMENTS THE RESULT IS TRUNCATED TO AN INTEGER AND THIS NUMBER OF SAMPLES IS PUT INTO EACH SEGMENT, FOR EXAMPLE, IF THERE ARE 36 SAMPLES IN THE UTTERANCE, AND THERE ARE 8 SEGMENTS, THEN EACH SEGMENT WILL HAVE 4 SAMPLES, AND THE LAST 4 SAMPLES WILL BE DISCARDED.

IN MODE TWO THE SUM OF THE ABSOLUTE ENERGY CHANGES BETWEEN THE CURRENT SAMPLE AND THE PREVIOUS SAMPLE FOR ALL FILTERS OR FOR ANY CONTIGUOUS SUBSET OF FILTERS IS DETERMINED FOR EACH SAMPLE AND ALSO ACCUMULATED OVER THE UTTERANCE. THE TOTAL ENERGY CHANGE IS DIVIDED BY THE NUMBER OF SAMPLES TO OBTAIN THE THRESHOLD FOR SEGMENTATION, THE UTTERANCE IS THEN DIVIDED UP SO THAT THE CUMULATIVE ENERGY CHANGES IN ALL SEGMENTS ARE EQUALIZED AS CLOSELY AS POSSIBLE.

IN MODE THREE THE SEGMENTATION IS DONE AS IN MODE TWO EXCEPT THAT THE SPECTRUM IS REPLACED BY ITS LOGARITHM BEFORE THE SEGMENTATION PROCESS. IN MODES TWO AND THREE THE FILTERS OVER WHICH THE ENERGY SUM IS TAKEN CAN BE SELECTED BY CHOOSING THE LOW AND HIGH FILTER NUMBERS FOR THE RANGE,

CODE MODE

THERE ARE A NUMBER OF MODES FOR THE CODING PROCESS AS FOLLOWS:

- 1-3-LEVEL INDEPENDENT
- 2-3-LEVEL CHAIN
- 3-2-LEVEL INDEPENDENT
- 4-2-LEVEL CHAIN
- 5-REDUCED RESOLUTION(INACTIVE)
- 6-3-LEVEL INDEPENDENT,MODIFIED THRESHOLD
- 7-INDIVIDUAL FILTER VS. AVERAGE, 3-LEVEL
- 8-INDIVIDUAL FILTER VS. AVERAGE, 2-LEVEL
- 9-REVISED COMPARISONS
- 10-REVISED COMPARISONS, MODIFIED THRESHOLD

IN MODE 1, THE FIRST 8 ELEMENTS OF THE CODE FOR EACH SEGMENT ARE DERIVED FROM COMPARISONS OF ADJACENT ELEMENTS OF THE DATA, I.E. 1 VS. 2, 3 VS. 4, ETC. THE NEXT 4 ELEMENTS OF THE CODE ARE DERIVED BY COMPARING TWO-ELEMENT SUMS OF THE DATA E.G. 1+2 VS. 3+4. TWO MORE CODE ELEMENTS ARE DERIVED FROM 4-ELEMENT DATA SUMS AND THE 15TH CODE ELEMENT IS DERIVED FROM 8-ELEMENT DATA SUMS, I.E. THE SUM OF 1 THROUGH 8 VS. THE SUM OF 9 THROUGH 16. EACH CODE ELEMENT IS 21 IF THE HIGHER ORDER ELEMENT OF THE DATA IS GREATER THAN THE LOWER ORDER ELEMENT BY A FACTOR OF 9/7

OR GREATER, 10 IF THE LOWER ORDER DATA ELEMENT IS GREATER BY THE SAME FACTOR, AND 00 IF NEITHER CONDITION HOLDS,

IN MODE 2, THE ELEMENTS ARE COMPARED 1 VS. 2, 2 VS. 3, 3 VS. 4, ETC TO PRODUCE A 30-BIT CODED RESULT. COMPARISONS ARE MADE AS ABOVE,

MODE 3-SAME AS MODE 1 BUT 2-LEVEL CODING

MODE 4-SAME AS MODE 2 BUT 2-LEVEL CODING

MODE 5 IS THE SAME AS MODE 1 EXCEPT THE FILTER RESOLUTION IS REDUCED BY COMBINING ADJACENT FILTERS. IN THIS MODE THERE ARE ONLY 7 ELEMENTS PER SEGMENT RATHER THAN 15,

MODE 6 IS THE SAME AS MODE 1 EXCEPT THAT THE THRESHOLD IS 17/15,

MODE 7 CREATES 16 ELEMENT CODE BY COMPARING 10 VALUE WITH SPECTRUM MEAN. COMPARISON IS AS ABOVE WITH THRESHOLD VALUE 9/7,

MODE 8 IS THE SAME AS MODE 7 EXCEPT 2-LEVEL. MODE 9 REPLACES ELEMENTS 7 AND 8 WITH NEW ELEMENTS DERIVED FROM COMPARISONS OF FILTERS 3+4 VS. 5+6 AND 4+5 VS. 6+7 RESPECTIVELY. ALSO A 16TH ELEMENT IS ADDED COMPARING FILTERS 2+3 VS. 4+5. CODE ELEMENTS ARE GENERATED AS IN MODE 1. MODE 10 IS THE SAME AS MODE 9 EXCEPT THAT CODE ELEMENTS ARE GENERATED AS IN MODE 6,

COMPARISON MODE

THERE ARE THREE COMPARISON MODES AS FOLLOWS:

1-TIME WARP

2-STRAIGHT

3-PLUS AND MINUS OFFSET

IN MODE ONE IN BOTH THE TRAINING AND RECOGNITION PROCESS THE CODED UTTERANCES TO BE COMPARED ARE MATCHED UP SEGMENT BY SEGMENT TO PRODUCE THE CLOSEST MATCH BY THE ITAKURA ALGORITHM.

IN MODE TWO THE SEGMENTS ARE SIMPLY COMPARED ONE FOR ONE IN ORDER. IN MODE THREE THEY ARE COMPARED IN ORDER AND ALSO SHIFTED ONE POSITION EITHER WAY TO PRODUCE THREE SCORES. THE HIGHEST SCORE IS SELECTED. THIS IS DONE ONLY IN THE RECOGNITION PROCESS.

REFERENCE PATTERN DISTANCE

THE ROUTINE PROVIDES FOR MULTIMODE TRAINING AND RECOGNITION IN THE FOLLOWING WAY. THE UTTERANCES TO BE USED FOR THE TRAINING SET ARE COLLECTED AND PROCESSED THROUGH THE CODING STAGE. THE MATRIX OF HAMMING DISTANCES BETWEEN ALL EXAMPLES IN THE TRAINING * ITAKURA, F., "MINIMUM PREDICTION RESIDUAL ALGORITHM APPLIED TO SPEECH RECOGNITION", IEEE TRANS. ACoust., SPEECH, SIGNAL PROCESSING, VOL. ASSP-24, PP.67-72, FEB. 1975.

SET IS THEN CALCULATED, AND FOR A GIVEN WORD THE EXAMPLES ARE GROUPED TOGETHER IN SETS SO THAT ALL MEMBERS OF EACH SET ARE WITHIN THE SPECIFIED REFERENCE PATTERN DISTANCE OF EACH OTHER. FOR EACH WORD THE NUMBER OF REFERENCE PATTERNS MAY RANGE FROM ONE TO THE NUMBER OF EXAMPLES IN THE TRAINING SET. AN EXAMPLE IN THE TRAINING SET MAY APPEAR IN MORE THAN ONE REFERENCE PATTERN. THE MULTIMODE ROUTINE CAN BE FORCED INTO A SINGLE MODE PROCESS BY SPECIFYING A REFERENCE PATTERN DISTANCE GREATER THAN THE MAXIMUM THAT CAN OCCUR, E.G. 1000. ALSO BY SPECIFYING THE DISTANCE TO BE ZERO, THE ROUTINE WILL PRODUCE A SEPARATE REFERENCE PATTERN FOR EACH EXAMPLE IN THE TRAINING SET.

SCORE MODE

THERE ARE THREE SCORING MODES:

- 1-LINEAR
- 2-EXPONENTIAL WEIGHTED
- 3-WEIGHTED ELEMENT

MODE THREE CAN BE USED ONLY WITH 3-LEVEL CODING PROCESSES. IN ALL MODES THE SCORE IS COMPUTED FOR EACH ELEMENT OF THE CODE NOT MASKED IN THE REFERENCE PATTERN, AND THE ELEMENT SCORES ARE SUMMED OVER THE UTTERANCE. THE ELEMENT SCORE IS $(2-D)$ FOR 3-LEVEL CODES AND $(1-D)$ FOR 2-LEVEL CODES, WHERE D IS THE HAMMING DISTANCE BETWEEN UNKNOWN AND REFERENCE ELEMENTS. IN MODE ONE THE ELEMENTS ARE SUMMED WITH UNIFORM WEIGHTING; IN MODE THREE ARBITRARY WEIGHTS CAN BE ASSIGNED TO ELEMENTS BY SPECIFYING A 15-ELEMENT WEIGHT VECTOR. THE MAXIMUM SUM OBTAINABLE IS $2 \times$ THE NUMBER OF UNMASKED ELEMENTS IN THE REFERENCE PATTERN (OR $1 \times$ THIS NUMBER IN THE CASE OF 2-LEVEL CODES). IN MODES ONE AND THREE THE SCORE IS 128 TIMES THE RATIO OF THE SUM OF ELEMENT SCORES TO THE MAXIMUM SCORE FOR THE REFERENCE PATTERN USED IN THE COMPARISON. IN MODE TWO THE SCORE IS EXPONENTIALLY WEIGHTED BY RAISING THE RATIO OF ELEMENT SCORE SUM TO MAXIMUM SUM TO THE POWER $60/NRV$ WHERE NRV IS THE NUMBER OF UNMASKED ELEMENTS IN THE REFERENCE PATTERN.

APPENDIX B
RECOGNITION RESULTS SUMMARY

The following table presents the results of all recognition experiments conducted on the program. An explanation of the columns is given in Table B-1.

TABLE B-1. KEY TO RESULTS DATA

<u>Col. No.</u>	<u>Heading</u>	<u>Description</u>
1		Record identification number
2	SUBJ	Subject number (See Table II)
3	REC	File number for recognition data (See Table B-2 for key)
4	G	G-force level of file in Col. 3
5	TRAIN	File number for training data
6	G	G-force level of file in Col. 5
7	PASS	Number of training passes
8	SEQ	Sequence numbers of training samples
9	SPRD	Period (in milliseconds) of sam- pling clock
10	PROC	Processing mode (See Appendix A)
11	CODE	Code mode (See Appendix A)
12	COMP	Comparison mode (See Appendix A)
13	SEGM	Segmentation mode (See Appendix A)
14	NSEG	Number of segments
15	FLTS	Filters used in energy change seg- mentation (See Appendix A)
16	SCR	Scoring mode (See Appendix A)
17-19	PREPROC-1,-2,-3	Preprocessing applied to data file (See Sec. 2.3.1.2)
20	REF PAT DIS	Threshold for separation of ref- erence patterns in multimode training (See Appendix A)
21	MN IN	Mean in-class score
22	MAX OUT	Mean of the largest out-of-class score
23	PI	Performance index (See Sec. 2.3.1.1)
24	RATE	Recognition rate

TABLE B-2. KEY FOR FILE NUMBERS

- TRF - Original files
- TRE - Same as TRF file of same number but edited to correct mis-labeled words
- TAF - Several TRF files of the same g-force level combined
- COL - Several files of same subject but different g-levels combined
- NRF - Original file - 2nd sampling. NRF and TRF files with the same number are not necessarily for the same original data
- BED - Manually edited for breath noise elimination

RECOGNITION RESULTS SUMMARY

[illegible]

[illegible]

[illegible]

REF	MIN	MAX	PI	RATE
204	50	100	96	85.6
205	50	100	96	85.5
206	50	100	96	85.5
207	50	100	96	85.5
208	50	100	96	85.5
209	50	100	96	85.5
210	50	100	96	85.5
211	50	100	96	85.5
212	50	100	96	85.5
213	50	100	96	85.5
214	50	100	96	85.5
215	50	100	96	85.5
216	50	100	96	85.5
217	50	100	96	85.5
218	50	100	96	85.5
219	50	100	96	85.5
220	50	100	96	85.5
221	50	100	96	85.5
222	50	100	96	85.5
223	50	100	96	85.5
224	50	100	96	85.5
225	50	100	96	85.5
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300	50	100	96	85.5

METRIC SYSTEM

BASE UNITS:

Quantity	Unit	SI Symbol	Formula
length	metre	m	...
mass	kilogram	kg	...
time	second	s	...
electric current	ampere	A	...
thermodynamic temperature	kelvin	K	...
amount of substance	mole	mol	...
luminous intensity	candela	cd	...

SUPPLEMENTARY UNITS:

plane angle	radian	rad	...
solid angle	steradian	sr	...

DERIVED UNITS:

Acceleration	metre per second squared	...	m/s
activity (of a radioactive source)	disintegration per second	...	(disintegration)/s
angular acceleration	radian per second squared	...	rad/s
angular velocity	radian per second	...	rad/s
area	square metre	...	m
density	kilogram per cubic metre	...	kg/m
electric capacitance	farad	F	A·s/V
electrical conductance	siemens	S	A/V
electric field strength	volt per metre	...	V/m
electric inductance	henry	H	V·s/A
electric potential difference	volt	V	W/A
electric resistance	ohm	...	V/A
electromotive force	volt	V	W/A
energy	joule	J	N·m
entropy	joule per kelvin	...	J/K
force	newton	N	kg·m/s
frequency	hertz	Hz	(cycle)/s
illuminance	lux	lx	lm/m
luminance	candela per square metre	...	cd/m
luminous flux	lumen	lm	cd·sr
magnetic field strength	ampere per metre	...	A/m
magnetic flux	weber	Wb	V·s
magnetic flux density	tesla	T	Wb/m
magnetomotive force	ampere	A	...
power	watt	W	J/s
pressure	pascal	Pa	N/m
quantity of electricity	coulomb	C	A·s
quantity of heat	joule	J	N·m
radiant intensity	watt per steradian	...	W/sr
specific heat	joule per kilogram-kelvin	...	J/kg·K
stress	pascal	Pa	N/m
thermal conductivity	watt per metre-kelvin	...	W/m·K
velocity	metre per second	...	m/s
viscosity, dynamic	pascal-second	...	Pa·s
viscosity, kinematic	square metre per second	...	m/s
voltage	volt	V	W/A
volume	cubic metre	...	m
wavenumber	reciprocal metre	...	(wave)/m
work	joule	J	N·m

SI PREFIXES:

Multiplication Factors	Prefix	SI Symbol
1 000 000 000 000 = 10 ¹²	tera	T
1 000 000 000 = 10 ⁹	giga	G
1 000 000 = 10 ⁶	mega	M
1 000 = 10 ³	kilo	k
100 = 10 ²	hecto*	h
10 = 10 ¹	deka*	da
0.1 = 10 ⁻¹	deci*	d
0.01 = 10 ⁻²	centi*	c
0.001 = 10 ⁻³	milli	m
0.000 001 = 10 ⁻⁶	micro	μ
0.000 000 001 = 10 ⁻⁹	nano	n
0.000 000 000 001 = 10 ⁻¹²	pico	p
0.000 000 000 000 001 = 10 ⁻¹⁵	femto	f
0.000 000 000 000 000 001 = 10 ⁻¹⁸	atto	a

* To be avoided where possible.

MISSION
of
Rome Air Development Center

RADC plans and conducts research, exploratory and advanced development programs in command, control, and communications (C³) activities, and in the C³ areas of information sciences and intelligence. The principal technical mission areas are communications, electromagnetic guidance and control, surveillance of ground and aerospace objects, intelligence data collection and handling, information system technology, ionospheric propagation, solid state sciences, microwave physics and electronic reliability, maintainability and compatibility.

